PRECIPITATION FEATURES ACCORDING TO THE
TROPICAL RAINFALL MEASURING MISSION

by

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ABSTRACT

Tropical Rainfall Measuring Mission (TRMM) satellite measurements from the precipitation radar and TRMM microwave imager have been combined to yield a comprehensive 3-year database of precipitation features (PFs) throughout the global tropics. This study presents an analysis of the diurnal cycle of the observed PFs’ rainfall amount, frequency, intensity, convective-stratiform portioning, and convective intensity. Over the oceans, the diurnal cycle of rainfall has a small amplitude, with the maximum contribution to rainfall coming from Mesoscale Convective Systems (MCSs) in the early morning. Land areas have a much larger rainfall cycle than over the ocean, with a marked minimum in the mid-morning hours and a maximum in the afternoon, decreasing through midnight. MCSs over land have a convective intensity peak in the late afternoon, however their rainfall peaks later (near midnight) due to their life cycle.

An evaluation of the version 5 Precipitation Radar (PR) and TRMM Microwave Imager (TMI rainfall products is performed as a function of system type using the PF algorithm. The evaluation is performed by comparing long term TRMM rainfall products with rain gauge analyses, as well as other rainfall estimates, and by directly comparing rainfall estimates from the PR and TMI within the PR swath. The TMI overestimates rainfall in most of the tropics and subtropics with respect to both the gauges and the PR. The PR estimates are generally higher than the TMI’s in midlatitude cold seasons, as well as in MCS dominated areas. The analysis by feature type revealed that the TMI overestimates relative to the PR are due to overestimates in
MCSs and features with appreciable 85 GHz ice scattering, with negative biases in precipitation features without appreciable ice scattering. The TMI’s distribution of rain rates in MCSs and features with ice scattering is biased high with respect to the PR mainly in PR-defined stratiform regions, while estimates from features without ice scattering are biased negatively with respect to the PR due to the TMI’s sensitivity and beam filling effects. This preliminary study shows that the development of a storm-identifying algorithm may reduce regime dependent biases in a microwave precipitation algorithm.
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CHAPTER 1

INTRODUCTION

The dataset that has been provided by the launch of the TRMM satellite has provided views into the spaceborne radar-derived structure of storms in regions hitherto unobserved. Not only are radar observations obtained from TRMM, but their collocated visible, infrared, and passive microwave brightness temperatures, as well as lightning flash rates can be measured from TRMM. These individual datasets alone provide an excellent way to examine the properties of tropical precipitating systems, but the synergy of all the datasets combined can yield a comprehensive, multi-instrument database of the properties of precipitating cloud systems in the tropics.

One major difficulty of dealing with a combined satellite dataset, such as that available from TRMM, is the cumbersome “fire hose” of data available to the user. The combined TRMM dataset is on the order of several terabytes of data per year, much too large of a dataset to examine on the fly. So, much work must be done to reduce the size of the data to make it useful, especially when using multiple years of data. Thus, a data mining exercise is the first step in creating a database of the TRMM data. In this vein, the “Precipitation Feature” (or PF) database was developed in the Tropical Convection Research Group at Texas A&M University, and implemented there; subsequently a three-year database was completed at the University of Utah. This database reduces the data storage requirements by more than a factor of 10.
The PF algorithm, at the time of this work, combines data from the PR, TMI, Visible and InfraRed Scanner (VIRS), and the Lightning Imaging Sensor (LIS) instruments using the PF algorithm, and is fully automated for processing remotely at NASA Goddard Space Flight Center, TRMM Science Data and Information System (TSDIS). Data is automatically transferred to the University of Utah every day. The database consists of two levels of data, the so-called “Level 1” data which are the original data compressed and stored without extraneous fields, and PFs identified and classified by their characteristics, and the “Level 2” data, which are basically a table of selected properties of the PFs in the database. The former dataset occupies about 100 gigabytes of disk or tape space per year, the latter dataset is on the order of 200 MB per year easily examined by a user on a desktop workstation.

The main feature of the database is that it identifies types of rainfall systems in the tropics (the reader is referred to Nesbitt et al. 2000 and Chapters 1 and 2 of this work for scientific discussion of the PF algorithm). The PF database has allowed the investigation of the general properties of PFs in the tropics (Nesbitt et al. 2000, Toracinta et al. 2002), examining the properties of hurricanes and comparing them with the intensity of generalized convection over land and ocean (Cecil et al. 2002a, Cecil et al. 2002b), examining intense convection in the Tropics (Yorty 2002), examining the regimes of convection over the western Amazon basin (Petersen et al. 2002) and Nepal Himalaya (Barros et al. 2003), examining the diurnal cycle of rainfall and convective intensity of PFs in the Tropics (Nesbitt and Zipser 2003 and Chapter 1 of this work), and examining the rainfall algorithms over South America (Mota 2002) and the tropics in general (Chapter 2 of this work).
CHAPTER 2

THE DIURNAL CYCLE OF RAINFALL AND CONVECTIVE INTENSITY
ACCORDING TO THREE YEARS OF TROPICAL RAINFALL
MEASURING MISSION MEASUREMENTS

Introduction

Our physical understanding of the diurnal cycle of precipitation and convective intensity is currently limited by our ability to observe and model the cycle itself. The same processes that govern the physics of clouds in general fundamentally dictate the diurnal modulation of precipitating systems. Despite this fact, our comprehension of the fundamental controlling physical mechanisms remains deficient. Limitations revolve around two fundamental issues: (1) our inability to observe and quantify the true Tropics-wide diurnal cycle of rainfall amount and convective intensity, and (2) the use of numerical model simulations that may have deficiencies that do not allow the true representation of the diurnal cycle. The first limitation has been caused by incomplete sampling and/or the use of indirect proxies for rainfall that substitute for the measurement of the quantities of interest. The second limitation above also suffers from our lack, until recently, of complete and comprehensive observational datasets that can be used to validate our conceptual and numerical models.
Mechanisms Behind the Diurnal Cycle

Most previous works comparing the tropical rainfall diurnal cycle over ocean and land surfaces agree that the amplitude of the diurnal cycle of rainfall rate over continents is larger than that over the open oceans (Gray and Jacobson 1977). However, studies conducted over different regions of the tropics have found significant differences in the character of the diurnal cycle, leading to different hypothesized causal mechanisms. Over land, many studies using surface rain accumulation (Wallace 1975; Gray and Jacobson 1977; Oki and Musiake 1994; Dai et al. 1999) and surface weather reports of precipitation frequency (Dai 2001) link the timing of the diurnal precipitation frequency maximum to afternoon boundary layer destabilization caused by daytime insolation. However, many studies note that there are land areas with midnight to early morning maxima of precipitation, which may be linked to local effects such as complex terrain and sea breeze circulations (Oki and Musiake 1994; Yang and Slingo 2000), or the long, nocturnal life cycle of Mesoscale Convective Systems (Wallace 1975; McAnelly and Cotton 1989; Dai et al. 1999; Sherwood and Wahrlich 1999).

Despite being smaller in amplitude than over-land areas, a substantial oceanic nocturnal maximum of precipitation has been shown by many studies of rain gauge accumulations (Lavoie 1963; Gray and Jacobson 1977), surface weather reports (Kraus 1963; Dai 2001), generally agree with proxies for surface rainfall like ground-based radars (Rickenbach 1996; Short et al. 1997) infrared (Short and Wallace 1980; Albright et al. 1985; Hall and Vonder Harr 1999; Chen and Houze 1997; Garreaud and Wallace 1997; Yang and Slingo 2000; Zudiema 2002) and microwave brightness temperatures (Chang et al. 1995; Imaoka and Spencer 2000). However, regional differences in the
rainfall diurnal cycle exist over the ocean also. Albright et al. (1985) found an afternoon maximum in cold cloud coverage in the South Pacific Convergence Zone (SPCZ), while McGarry and Reed (1978) and Reed and Jaffe (1981) show afternoon maxima over the western Atlantic Ocean near the African coast. Near-continent variations in the diurnal cycle have been linked to coastline effects and gravity wave forcing by the nearby continental diurnal cycle (Silva Dias et al. 1987; Yang and Slingo 2000).

Away from the influence of continents, the cause for the observed diurnal cycle of precipitation over the open ocean remains debatable not well known and currently under discussion. One mechanism, first proposed by Gray and Jacobson (1977), emphasizes the dynamical consequence of the differential radiative heating between the convective and surrounding cloud-free region producing a daily variation in the horizontal divergence field, modulating the convection. A second mechanism (e.g., Cox and Griffith 1979; Webster and Stephens 1980; Randall et al. 1991) explains the afternoon minimum of oceanic precipitation through the absorption of short-wave radiation by the upper portions of the convective anvils, which increases the static stability in the cloudy regions, weakening vertical motions. Conversely, long-wave cooling at night decreases the stability, leading to enhanced convection. A third mechanism may be that nighttime long-wave cooling may increase relative humidities sufficiently everywhere that the effects of entrainment are reduced, and cloud development is favored at night (Dudhia 1989; Tao et al. 1996; Dai 2001). A fourth, more complex mechanism is linked to the daily variations in the surface layer over the ocean; Sui et al. (1997) and Chen and Houze (1997) show that an afternoon maximum
in ocean skin temperature corresponds with the generation of new convection in the calm Pacific warm pool region. A minimum in convection follows the next day in the convective wakes due to depletion of the local moist static energy and shading of the ocean from short-wave fluxes. Atmospheric tides have also been discussed as a diurnal modulator of low level convergence and rainfall (Malkus 1964; Brier and Simpson 1969; Dai 2001), however Lindzen (1978) has shed doubt on this hypothesis.

None of these mechanisms are necessarily exclusive in acting to modulate the diurnal cycle, making it difficult to separate them in an observational dataset. Numerical model studies using Cloud Resolving Models (e.g., Xu and Randall 1995; Tao et al. 1996; Liu and Moncrieff 1998; Sui et al. 1997) and General Circulation Models (e.g., Randall et al. 1991; Lieberman et al. 1994; Lin et al. 2000) have been a useful to attempt to diagnose the aforementioned causes of the diurnal cycle of convection over the Tropics. While these models allow a unique test bed to examine the physics of the diurnal cycle of precipitation, errors in model physics (radiation, microphysics or convective parameterizations for example) may lead to inappropriate conclusions about the true causes of the diurnal variation (Randall et al 1991, Lin et al. 2000, Yang and Slingo 2000). Due to the subtle differences in numerical model simulations and observational datasets both in situ and remotely-sensed, the question as to which of these mechanisms dominates the physics behind the diurnal cycle in a particular location or meteorological regime remains an open one.

The launch of the TRMM satellite in November 1997 allows data from the first quantitative spaceborne rain radar, the precipitation radar (PR) to be combined with data from the nonsun-synchronous TRMM microwave imager (TMI). The TRMM
platform provides the first three-dimensional snapshots of the radar reflectivity field and coincident passive microwave brightness temperatures of precipitating systems’ structures from space. While also measuring a remote sensing proxy for rainfall like measurements made from IR and microwave radiometers, the TRMM PR’s 2A25 reflectivity-rain rate algorithm can provide a more physically direct measurement of near surface rainfall than other remote-sensing proxies like IR cloud top temperatures (which may or may not be related to surface rainfall) and low-frequency microwave brightness temperatures (which are available only over ocean and are proportional to the optical depth of the rain layer). Convective intensity can also be inferred from the radar reflectivity profiles and 85 GHz microwave ice-scattering signatures provided by TRMM.

Despite the benefit of high spatial resolution (4.3 × 4.3 km at the satellite’s nadir point), temporal sampling is reduced when compared to IR satellite measurements or hourly surface reports. Since each overpass of a given location by the PR’s narrow (215 km) swath occurs infrequently (~0.5 to 2 times per day), long time composites of rainfall estimates must be constructed from the TRMM estimates in order to reconstruct the diurnal cycle of rainfall with sufficient sampling. However, once these composites are created, they may be used to infer the diurnal cycle of radar-estimated rainfall and convective intensity consistently and quantitatively tropics-wide. The precipitation feature (PF) algorithm described in Nesbitt et al. (2000) is applied to obtain these parameters for differing types of PFs ranging from small systems to large MCSs, allowing a tropics-wide quantification of the observed diurnal cycle of rainfall and convective intensity by rainfall system type.
Data and Methods

The TRMM Satellite

This study uses data from the TRMM satellite’s PR and TMI, extending temporally from December 1997 through November 2000. Kummerow (1998) and Kummerow et al. (2000) detail the specifications of the PR and TMI instruments aboard the TRMM satellite employed in this study. Briefly, the PR is a three-dimensional spaceborne precipitation radar that, at its nadir point, has $4.3 \times 4.3$ km horizontal resolution and a vertical resolution of 250 m. The PR retrieves reflectivities at a frequency of 13.8 GHz from the surface to 20 km above the earth ellipsoid. It has a 215-km swath width with a minimum detectable signal of nearly 17 dBZ (which limits the sensitivity of its rain estimates to about 0.5 mm hr$^{-1}$). This study uses the algorithm 2A25 and 2A23 (version 5$^2$) attenuation-corrected reflectivity profiles and derived near surface rain products (readers are referred to Iguchi et al. 2000 for details on the 2A25 reflectivity-rain rate algorithm). Absolute errors in a given PR 2A25 near surface rainfall estimate may be introduced due to uncertainties in the attenuation correction, drop-size distribution, and nonuniform beam filling assumptions. However, it is unlikely that these errors are large, or would significantly affect our results portraying the relative phase and amplitude of the diurnal cycle; this study seeks only to examine the daily relative variations in rainfall, etc.

The TMI is a 9-channel, 5-frequency, elliptically scanning passive microwave radiometer. It has a viewing angle of $53^\circ$ off nadir, a 760-km swath width, and

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$^1$ Instrument specifications correspond to the pre-TRMM altitude boost, which occurred in August 2001.

horizontal resolutions of 5 km × 7 km at 85 GHz (resolution is constant across the entire swath). Polarization corrected temperatures (PCTs, Spencer et al. 1989) have been calculated at 85 GHz to remove effects of the radiometrically cold ocean and non-uniform surface emissivities over land surfaces:

\[ PCT = \frac{\beta T_{h\nu} - T_{h\sigma}}{\beta - 1}. \]

The horizontally- and vertically-polarized channels are used (\(T_{h\nu}\) and \(T_{h\sigma}\), respectively) to calculate 85 PCT; the value for \(\beta\) is 0.45 at 85 GHz (Spencer et al. 1989). While PCTs in this frequency range may be warmed by as much as 10° by emission from supercooled cloud liquid water (Toracinta et al. 2002), they are a good indication of the scattering optical depth of precipitation-sized ice particles within a cloud system, and the ability of the attendant convection to produce such ice particles. As with the PR products, the version 5 TMI products (algorithm 1B11) are employed in this study.

The PF Algorithm

The PF algorithm defined in Nesbitt et al. (2000) is used to identify individual storms within the combined TRMM dataset. PR and TMI data are collocated within the 215-km wide PR swath to identify contiguous areas of PR rainfall and TMI 85-GHz ice scattering. A nearest-neighbor matching technique was used to match the two datasets, meaning that every PR pixel was matched with the nearest TMI pixel, with the PR used as the base grid. The PF areas were required to be at least four PR pixels in size (~75 km\(^2\)) and to contain either PR near-surface reflectivities ≥ 20 dBZ or 85 GHz PCT ≤
250 K. The PFs were then classified by their radar and ice scattering properties into three categories:

- PF without ice scattering (no pixels containing PCT $\leq 250$ K at 85 GHz), likely “warm rain” features too shallow or those too small to contain significant ice scattering at TMI resolution;
- PF with ice scattering (at least one pixel with 85 GHz PCT $\leq 250$ K), these are features with significant optical depths of ice aloft, but are not large or intense enough to meet the MCS category;
- PF with a MCS (PF contained at least 2000 km$^2$ of contiguous area with 85 GHz PCT $\leq 250$ K and 185 km$^2$ $\leq 225$ K), defined to ensure a large convective system analogous to the Mohr and Zipser (1996) and Houze (1993) ice scattering and radar MCS definitions, respectively.

Fig. 1 shows a schematic of these three types of features showing idealized PR radar reflectivity and TMI 85 GHz brightness temperatures. Maintaining that PFs are at least 4 pixels in size containing near-surface reflectivities $\geq 20$ dBZ means that about 19% of the total raining pixels are not accounted for (between the PR minimum detectable signal of 17 and 20 dBZ and PF size between 1 and 4 pixels), however only about 4% of the total 2A25 near-surface rainfall is missed.

Composites of the diurnal cycle are created by converting the time of observation (in UTC time) of a particular PF to local time based on its longitude. The PF’s characteristics at the pixel level (type of PF, rainfall, PR profiles, and TMI brightness temperatures) are then binned in the appropriate local time bin. The location of each PF is determined by its centroid location (using the technique of Mohr and
Figure 1. Vertical cross-section schematic of the three PF types (adapted from Nesbitt et al. 2000 and Nesbitt and Zipser 2003).
Zipser 1996). Note that the land-ocean mask used in this study comes from the 2A25 “method flag” (with a native 1 km resolution); each PF is assigned a land or ocean value based on the majority number of pixels in each PF being over land or ocean (with features with equal numbers of land and ocean pixels going to land). Land versus ocean composites in Sections 4 and 5, and the regional analyses in Sections 6b and 6c use this high resolution land-ocean mask in their creation. Composites for the 10° x 10° boxes described in Section 6a use the centroid position of the PF to determine which grid box the PF is assigned to.

**Sampling Issues**

The TRMM satellite orbits with an inclination of 35°, providing data between approximately ±36° latitude. However, the narrow swath of the PR data (215 km) leads to geographic undersampling on a daily basis. The orbital pattern of the satellite allows sampling between 0.5 times per day at the equator to nearly 2 times per day at 35° latitude. In addition, it takes about 23 days for the TRMM satellite to return to a given position at a given local time. Therefore, in order to sample the complete diurnal cycle at a particular location, it is necessary to composite a time span of data to allow the statistics of nonlinear fields like rainfall to converge at a particular location. Lin et al. (2000) found that at least 3 months of PR data must be combined to adequately sample a 4° x 5° grid at 1-hr resolution. To test the statistical robustness of our method at its minimum confidence level, we have compiled three months of NOAA-Climate Prediction Center (CPC) hourly rain gauge data (Higgins et al. 1996) over the Southeast United States (2.5° longitude by 2° latitude grids over land, east of 90°W and south of 35°N over land, similar to the analysis of Dai et al. 1999) during June, July and August.
1998. Fig. 2 shows the diurnal cycle (in 2-hr bins) of normalized rainfall amount from TRMM PFs over the same area and time period (solid line). Also plotted is the coincident NOAA-CPC normalized rainfall amount and frequency (hours with greater than 0.1 mm hr\(^{-1}\) rain accumulation). Normalized is defined as dividing the bin totals by the daily mean value. The TRMM rainfall data generally follow the trend of the gauge data for both phase and amplitude given the constraints of sampling mentioned above. Aware of this sampling constraint, in this paper we examine the diurnal cycle from relatively large areal composites of TRMM data combined into a three-year composite (December 1997-November 2000) with no less than 2-hr bin temporal resolution and 10° x 10° spatial resolution. Because of these sampling issues, investigation of the diurnal cycle on smaller geographic (< 10° x 10° grids) and temporal scales (i.e., seasonal) will await the accumulation of more data. For a comprehensive seasonal analysis of the diurnal cycle of precipitation frequency from surface weather reports, the reader is referred to Dai (2001).

Variability of rainfall also occurs on longer timescales other than diurnally. Nondiurnal rainfall enhancements from passing easterly wave disturbances, mid-latitude shortwave troughs, and other phenomena like the Madden-Julian oscillation are aliased in our long-term averages. No attempts to remove these variations caused by these phenomena are made in our results, nor are the phenomena believed to significantly alter our conclusions. Examination of variability on these timescales is left for future work.

\(^3\) Quality-controlled hourly gridded rainfall data over the US are available only through calendar year 1998 at the time of submission.
Figure 2. The diurnal cycle of TRMM Precipitation Feature rainfall (solid), CDC Gauge Rainfall (dash), and Rain Frequency (dash-dot) over the southeast US, normalized to the daily mean amplitude. See text for details.
Examples of Diurnal Variability from TRMM

The Maritime Continent region in Southeast Asia represents a unique geographic region that contains large islands, narrow peninsulas, and complex terrain surrounded by large oceanic and continental areas. As a result, effects applicable both to the large-scale and local effects drive the diurnal cycle of PFs (c.f. Williams and Houze 1987, Oki and Musiake 1994). Fig. 3 is a plot of the diurnal variability of three years (all seasons) of sampled PFs with ice scattering (gray dots) and PFs with MCSs (black crosses) in the Maritime Continent region split into 4-hr time bins for each panel of the plot. During the late morning hours (0800-1200 LT), the land areas are largely devoid of PFs relative to the surrounding ocean regions. Four hours later (1200-1600 LT), many PFs with ice scattering appear over the islands and continental regions, with enhancements along the coasts (associated with sea-breeze effects) and mountain ranges (esp. along the higher terrain in New Guinea). Progressing to 1600-2000 LT, these features continue to be focused over land areas, with PFs with MCSs appearing likely because of upscale growth from smaller features earlier. Also, note the suppression of features just offshore resulting from subsidence from sea breeze circulations. Later (2000-0000 and 0000-0400 LT), the ratio of PFs with MCSs to those with ice scattering is increased over land due to the loss of daytime convective instability and increased convective organization there. By 0400-0800 LT, the number of features over land is returning to the levels in the first panel discussed. Note that throughout the day, there are much smaller diurnal cycle variations over isolated ocean areas than over-land areas. As shown below, this small diurnal variation in the number of features controls a similarly small diurnal variation in oceanic rainfall.
Figure 3. The locations of PFs with ice scattering (dots) and MCSs (small crosses) in the Maritime Continent region. Each of the six panels (a through f) displays a four hour time bin (local time) as labeled.
Figure 3. (continued)
Figure 3. (continued)
Land and Ocean Differences in the Diurnal Cycle

The Diurnal Rainfall Budget

This section seeks to describe the bulk characteristics of the Tropics-wide diurnal cycle of rainfall from PFs. Figs. 4 and 5 show several characteristics (broken into 2-hr bins) of the diurnal cycle of PFs by type over land (Fig. 4) and ocean (Fig. 5) areas. The upper left panels (a) plot the retrieved 2A25 volumetric rainfall (mm hr\(^{-1}\) km\(^2\)) by feature type. Volumetric rainfall is a parameter defined by Mohr et al. (1999) that sums average rain rates for each PF in volume per unit time (L\(^3\)T\(^{-1}\) in MKS units), rather than average depths per unit time as in rain accumulations in mm hr\(^{-1}\) (LT\(^{-1}\)). This statistic is used because instantaneous rain rates are scarcely unique across the spectrum of PFs; examining rain volumes allow the diagnosis of rainfall budgets in a given situation. The shading of the bars indicates the type of feature plotted. The upper right panels (b) plot the number of features by type in each graph. The lower left panels (c) show the diurnal cycle of median area for each feature type; the lower right panels (d) indicate the mean conditional rain rate (mm hr\(^{-1}\)) for each type of feature (which is simply the mean rain rate within the raining area of each type of system).

All three types of PFs modulate the diurnal cycle of rainfall over land (Fig. 4a). There is a sharp early afternoon peak in over-land rainfall (around 1500 LT, similar to the global results of Dai 2001), enhanced by a peak in rainfall from PFs with and without ice scattering which both peak at this time. Non-MCS features yield a relative minimum of precipitation in the morning around 0900 LT, which also coincides with a diurnal minimum in the total rain. The distinct minimum around 0900 LT does not appear in the global analysis of Dai (2001); however it does appear in several regional
Figure 4. Diurnal rainfall and other characteristics of PFs in the database over land within +/-36° latitude. The shading of the bars or line style represents the feature type indicated in the legend. Each panel displays the following characteristics of the diurnal properties of the rainfall budget by PF type: (a) total volumetric rainfall, (b) total number of features observed, (c) median area, and (d) mean conditional rain rate.
Figure 4. (continued)
Figure 4. (continued)
Figure 4. (continued)
Figure 5. Diurnal rainfall and other characteristics of PFs in the database over ocean within +/-36° latitude. The shading of the bars or line style represents the feature type indicated in the legend. The each panel displays the following characteristics of the diurnal properties of the rainfall budget by PF type: (a) total volumetric rainfall, (b) total number of features observed, (c) median area, and (d) mean conditional rain rate.
Figure 5. (continued)
Figure 5. (continued)
Figure 5. (continued)
studies (e.g., the “inland” regime of Oki and Musiuke 1994; Garreaud and Wallace 1997). PFs with MCSs do not peak in rainfall contribution in the early afternoon: their peak occurs in a broad 6-hr peak centered on 0100 LT. PFs with MCSs yield a relative minimum of precipitation around noon LT.

To examine which factors control the diurnal cycle of rainfall, an analysis is performed of the contributing characteristics of the features by type. Total volumetric rainfall ($\sum R_{vol}$) can be expressed as the product of three parameters:

$$\sum R_{vol} = \overline{RR}_{cond} \cdot \overline{A} \cdot n.$$  

These parameters are mean conditional rain rate ($\overline{RR}_{cond}$), mean area ($\overline{A}$), and total number of features ($n$). These parameters are plotted in the remaining three quadrants of Figures 4 and 5 (except median area is plotted because of PF area’s roughly lognormal distribution, see Nesbitt et al. 2000 Fig. 5).

PFs with and without ice scattering over land diurnally vary in number (Fig. 4b) and mean conditional rain rate (Fig. 4d) in a similar fashion as their total volumetric rainfall (all peaking in the early afternoon). This is offset somewhat by a lessening of median PF area in the early afternoon for these feature types (Fig. 4c). Thus, increased numbers of systems containing higher rain rates control the diurnal rainfall cycle for over-land PFs with and without ice scattering. This finding is in contrast with the findings of Dai et al. (1999) using hourly rain gauge data, who find that over the southern US conditional rain rates remain more or less constant throughout the day. This is possibly due to differing geographic areas studied, but more likely due to the differing data types used in these studies. Heavy, short lived, convective rain rates can
be aliased in with lighter, longer duration rain events in hourly data, whereas instantaneous measurements (like those derived from the PR) can record these convective rain events. This leads to a low bias in hourly gauge conditional rain rates with respect to remote sensing estimates, which are closer to the true instantaneous rain rate.

PFs with MCSs have distinctly different factors contributing to their total volumetric rainfall. Mean conditional rain rates remain nearly constant throughout their daily cycle (Fig. 4d). The number of MCSs peaks in the evening (1700-1900 LT) as shown by Fig. 4b, slowly decreasing to a relative minimum in the late morning (around 1100 LT). In contrast, the median area (Fig 4c) steadily increases from a minimum in the late afternoon (centered around 1600 LT) to a maximum around 0900 LT. Thus, the broad peak in over-land MCS rainfall centered on 0100 LT (Fig 4a) is contributed to by a balance of a decreasing number of systems that increase in area from evening to early morning. This result is similar to the over-land mesoscale convective complex diurnal cycle found by Laing and Fritsch (1997).

The magnitude of the oceanic diurnal cycle of total rainfall (Fig. 5a) is considerably less than that over land areas, varying by a maximum-minimum ratio of 1.3:1 over oceanic areas versus a ratio of 2.25:1 over land areas. The total rainfall reaches a maximum near sunrise (nearly 0600 LT). Unlike land areas, all oceanic PF types peak in rainfall contribution in the early AM hours, with peaks at 0300, 0300, and 0700 LT for PFs without, with, and with MCSs, respectively. For features with and without ice scattering, the peak at 0300 LT is only caused by a maximum in their count at that time (Fig. 5b); median area (Fig. 5c) and mean conditional rain rates (Fig. 5d) do
not contain any appreciable diurnal cycle. A secondary peak in rainfall from features
with ice scattering in the afternoon also corresponds to a peak in the number of features
in the early afternoon. The later peak in MCS rainfall around 0700 LT (similar to the
results of Mapes and Houze 1993) is contributed by a peak (near 0500 LT) and slow
decrease in the number of systems (Fig. 5b), and a slow increase in MCS area around
sunrise peaking near 1100 LT (Fig. 5c). Therefore, the diurnal cycle of rainfall over the
ocean is almost completely due to an increase of the number of systems, not the rain
rates contained in them. This is similar to the pattern derived from surface weather
reports derived in (Dai 2001). For oceanic MCSs, there is also a contribution from
systems expanding in area through the early morning, delaying their rainfall maximum
to 0700 LT, slightly later than the peak in the number of MCSs about 2 hr earlier.

Mean conditional rain rates (Fig. 5d) for oceanic MCSs remain constant like
their over-land counterparts (Fig 4d). Note that the oceanic mean conditional rain rate
value of around 4.8 mm hr\(^{-1}\) is less than the mean value of nearly 5.7 mm hr\(^{-1}\) over land.

The Diurnal Cycle of Convective and Stratiform Rainfall

The PR algorithm 2A23 contains a rain type (i.e., convective-stratiform)
classification\(^4\); this is employed here to examine the diurnal variation in the structure of
the PFs by type. While any scheme of this sort sometimes misclassifies rain type (see
Biggerstaff and Listemaa 2000), convective and stratiform rain identification has
important implications on determining net heating and divergence profiles within
precipitating systems (Houze 1997), thus affecting estimates of their convective heat
and moisture budgets.

\(^4\) Details of the 2A23 algorithm can be found on the web at http://trmm.gsfc.nasa.gov/2a23.html.
Figs. 6 and 7 show the diurnal cycle by system type of land and ocean rainfall identified as convective and stratiform “certain” and “probably” by the 2A23 algorithm over land and ocean, respectively. Total diurnal cycle of stratiform rain over land (Fig. 6a) follows a pattern out of phase (having a broad peak at night) with the diurnal cycle of convective rain (Fig. 6b). This result agrees with the over-land diurnal cycle of “nonshowery” and “showery” weather reports presented in Dai (2001). When breaking down the results by feature type over land, however, the diurnal cycle of stratiform and convective rain is different. For PFs with and without ice scattering over land (Fig. 6, a and b), both stratiform and convective rainfall peak in the afternoon, with the diurnal cycle of convective rainfall having a larger relative variation from maximum to minimum. For MCSs over land, convective rainfall (Fig. 6b) increases to a nearly constant value between 15 LT and 01 LT, then slowly decreases throughout the early morning hours towards a relative minimum value at 09 LT. Stratiform MCS rainfall (Fig. 6a) slowly increases through the afternoon and evening from a minimum around 13 LT and remains nearly constant overnight between 23 and 07 LT, with a sharp decrease just after local sunrise. Fig. 6c shows that all three types of features peak in their fraction of rainfall convective in the afternoon. For features with and without ice scattering, this convective peak corresponds with a peak in total rainfall (Fig. 4a); MCS features’ stratiform rainfall causes the peak in total rainfall to lag until after midnight (Fig. 4a). Over land, the mean conditional rain rates remain nearly constant in convective and stratiform pixels (Fig. 6d). With convective and stratiform conditional rain rates constant throughout the day, the afternoon increases in total conditional rain rate (Fig. 4d) is due to an increase in convective rainfall fraction (Fig 6c), not an
Figure 6. Diurnal stratiform/convective characteristics of PFs in the database over land within +/- 36° latitude. The shading of the bars or line style represents the feature type indicated in the legend. The each panel displays the following characteristics of the diurnal properties of the rainfall budget by PF type: (a) total stratiform volumetric rainfall, (b) total convective rainfall, (c) fraction of PF rainfall classified as convective, and (d) mean conditional rain rate in convective (thick lines) and stratiform (thin lines and symbols) pixels.
Figure 6. (continued)
Figure 6. (continued)
Figure 6. (continued)

(d.)

Conditional Rain Rate (mm hr$^{-1}$)

Local Time

MCS convective
w/ice convective
w/o ice convective
MCS stratiform
w/ice stratiform
w/o ice stratiform
Figure 7. Diurnal stratiform/convective characteristics of PFs in the database over ocean within +/- 36° latitude. The shading of the bars or line style represents the feature type indicated in the legend. The each panel displays the following characteristics of the diurnal properties of the rainfall budget by PF type: (a) total stratiform volumetric rainfall, (b) total convective rainfall, (c) fraction of PF rainfall classified as convective, and (d) mean conditional rain rate in convective (thick lines) and stratiform (thin lines and symbols) pixels.
Figure 7. (continued)
Figure 7. (continued)
Figure 7. (continued)
increase in the rain rates in convective or stratiform pixels.

Over the oceans, the partition of rainfall among stratiform and convective-identified areas is nearly equal (Fig. 7, a and b). Both stratiform and convective rainfall peak with the total rainfall around 0500 to 0700 LT, consistent with the analysis of Dai (2001). The fraction of convective rainfall (Fig 7c) remains nearly constant at just above 50% for all feature types throughout the diurnal cycle over the ocean.

Mean conditional rain rates remain constant for both convective and stratiform areas, for all feature types over both land and ocean (Figs. 6d and 7d). Total conditional rain rates over land increase (Fig 4d) because the fraction of rain from convective pixels increases (Fig. 6c). From a convective/stratiform perspective over land, the increase in total rainfall in the afternoon is controlled by more systems that also contain a higher convective fraction (consistent with the destabilization hypothesis of Wallace 1975), thus increasing rainfall. MCSs’ convective rainfall is replaced by stratiform rainfall as the nighttime hours progress. This transition from heavier convective rain rates to lighter stratiform rainfall is offset by increasing median MCS area. These offsetting trends in the rainfall budget lead to a slow decrease in rainfall through the early morning.

Over the ocean, convective fractions (Fig. 7c) and mean conditional rain rates (both total and convective/stratiform) are constant. This relates that it is not raining harder during the nighttime hours; the predawn rainfall maximum is caused by systems raining over a larger total area (caused by an increase in the number of systems). This leads us to clarify the current hypotheses, restricting them not to imply that the direct radiation or dynamics-radiation feedback mechanisms increase rainfall by increasing
convective intensity or rain rates: they merely make the environment more favorable for the occurrence and bulk areal coverage of precipitating systems at night. Nighttime conditions do not generate significantly heavier rain rates in this dataset.

The Diurnal Cycle of TRMM-estimated Convective Intensity

Several studies have used the TRMM satellite to examine proxies for convective intensity of precipitating systems in the Tropics (Nesbitt et al. 2000; Short and Nakamura 2000; Boccippio et al. 2000; Petersen and Rutledge 2001; Toracinta et al. 2002; DelGenio and Kovari 2002). The PF algorithm also allows examination of remote sensing storm peak intensity parameters that may be used to examine the convective diurnal cycle (see Nesbitt et al. 2000 for a more complete description of each): minimum 85 GHz PCT and maximum height of the 30 dBZ echo.

Brightness temperature depressions in the microwave regime rely on a complex interaction between ice hydrometeor phase and bulk density, particle size distribution, number concentration, and the total scattering depth of the ice layer (Vivekanandan et al. 1991). Radiative transfer calculations indicate that brightness temperature depressions at 85 GHz are most sensitive to scattering by precipitation-sized ice particles greater than a few hundred micrometers in size. Here two indicators of maximum observed convective intensity within each system are presented (minimum 85 GHz PCT, maximum 30 dBZ echo top height). While these peak ice scattering and radar reflectivity parameters do not account for the areal coverage of intense pixels within each system (which may be correlated to bulk parameters like total latent heating, for example), they do quantify an upper limit to the convective vigor that is possible in a given region (and are likely correlated with parameters such as maximum updraft
strength and lightning probability). Evidence has associated these remote sensing proxies with peak convective intensity by many studies; the reader is referred to the introduction of Nesbitt et al. (2000) for a more complete discussion. Quantifying the diurnal cycle of convective intensity will provide an important validation of the diurnal variation of other observational parameters of precipitating systems like lightning (e.g., Petersen et al. 1996) which are highly related to measures of peak convective intensity.

Figs. 8 through 10 show cumulative distribution functions (CDFs) of PF intensity parameters for each type of feature over land and ocean; the contour levels for each intensity parameter indicate the percentile of intensity for the sample observed during that time bin. The data have been placed into 2 hr bins. Extreme values in the database are plotted with the thick line.

Fig. 8 shows the diurnal variation of the peak intensity parameters for PFs without ice scattering. Over the ocean (Figs. 8 a and c), there is strikingly little diurnal variation in both measures of convective intensity. Over land (Fig. 8, b and d), there is a notable mid- to late afternoon maximum in remotely-sensed convective intensity in the maximum heights of the 30 echo distribution. Brightness temperatures at 85 GHz show slightly more intense ice scattering in the nighttime hours, likely indicating surface and beam filling contamination from these weak, optically thin and/or small features mixed with background radiation.

PFs’ with ice scattering convective intensity parameters are plotted in Fig. 9. Again, there is very little diurnal variation in the intensity parameters over the ocean (Fig. 9, b and d). However, over land, a marked afternoon trough (ridge) in minimum
Figure 8. PF without ice scattering time-intensity CDFs of convective intensity. Minimum 85 GHz PCT over ocean (a) and land (b), maximum height of the 30 dBZ echo over ocean (c) and land (d). Extreme values are denoted by the thick line.
Figure 9. PF with ice scattering time-intensity CDFs of convective intensity. Minimum 85 GHz PCT over ocean (a) and land (b), maximum height of the 30 dBZ echo over ocean (c) and land (d). Extreme values are denoted by the thick line.
Figure 10. PF with MCS time-intensity CDFs of convective intensity. Minimum 85 GHz PCT over ocean (a) and land (b), maximum height of the 30 dBZ echo over ocean (c) and land (d). Extreme values are denoted by the thick line.
85 GHz PCT (maximum 30 dBZ echo top heights) are indicative of stronger convection during the afternoon. Over-land ice scattering intensity at 85 GHz peaks in intensity later (around 1700 LT) in general than radar-reflectivity measures (around 1500 LT); this lag is likely indicative of upscale growth of the anvil of these systems. Strong, high-reflectivity updrafts (raising echo top height distributions) create and subsequently loft large concentrations of precipitation-sized ice particles into the anvil (depressing ice scattering brightness temperatures). There also exists an apparent phase shift depending on intensity in each measure; for example features in the 20th and 30th percentile of maximum 30 dBZ heights peak in intensity around 1500 LT, while features in the 80th and greater percentiles peak around 1700 LT. Around sunrise, all parameters over land in the roughly 80th percentiles and less assume values roughly equal to the median oceanic values, whereas during the period of daytime insolation they become increasingly intense.

Fig. 10 presents the diurnal cycle of convective intensity from MCSs. Again, the convective intensity of MCSs over ocean is quite steady throughout the day. From the minimum 85 GHz PCT (Fig. 10a) and maximum height of the 30-dBZ (Fig. 10c) echo distributions, it appears as though over ocean there may be a slight preference for more intense ice scattering and radar reflectivity profiles in the early morning hours. Over land, convective intensity is again maximized in the mid-afternoon (Fig. 10, b and d), due to the presence of more extensive and optically thick volumes of ice (graupel and hail) in MCSs at that time.

None of the measures of oceanic maximum convective intensity show an appreciable convective intensity diurnal cycle. This is corroborative evidence to show
that peak convective processes (along with constant convective area fraction as mentioned above) are not invigorated over the ocean during the early morning rainfall maximum. The rainfall maximum is due to a larger number of systems, as discussed previously, not differing convective intensities or heavier rain rates within oceanic systems. Over land, afternoon convective processes are more intense and extensive (leading to decreased beam filling effects); these effects along with increased convective rain fraction (and thus higher total conditional rain rates), and numbers of features increases rainfall in the afternoon, especially for sub-MCS features where convective rainfall dominates the diurnal cycle.

**Regional Characterization of PFs’ Diurnal Cycle**

The characterization of the general properties and variation of the diurnal cycle of PFs on a regional basis is important in diagnosing regional precipitation and latent heating estimates from observations and numerical models, which have a direct link to our understanding of the general circulation (e.g., Hartmann et al. 1984). The PF database has been subsetted here to examine the regional variability of the diurnal cycle.

**Tropics-wide Phase and Amplitude of the Diurnal Cycle**

Fig. 11 shows the diurnal cycle of rainfall from PFs by type in 10° x 10° grid boxes. The amplitude and phase (in local time) of the first Fourier component of rainfall are shown, with the amplitude defined as the ratio of the maximum of the Fourier fit to the mean daily volumetric rainfall in each box; phase is simply the time of the maximum of the Fourier fit. In panel (a), MCS rain areas with less than $2.5 \times 10^6$
Figure 11. The diurnal cycle of rainfall amplitude (shading) and phase in hours of local time (arrows) from PFs by type. (a) PFs with MCSs, (b) PFs with ice scattering, (c) PFs without ice scattering. Amplitude and phase are defined as the percentage variation and time of maximum in the first Fourier component of the rainfall within each 10° × 10° box, respectively. MCS grid boxes in (a) containing less than 2.5 × 10^6 mm hr^{-1} km^2 volumetric rain have been screened due to insufficient sampling.
mm hr$^{-1}$ km$^2$ volumetric rainfall have been empirically screened due to insufficient numbers of MCSs in the given region. Over most open ocean boxes, the phase of the rainfall maximum is within a few hours of 06 LT, especially in the deep tropics. The subtropical oceans contain some exceptions, likely due to the forcing of MCSs being more synoptic in nature. A large fraction of continental boxes contain MCS maxima within a few hours of midnight, while many northern hemisphere subtropical land areas (like the United States and Asia) contain late afternoon maxima. The diurnal MCS rainfall amplitudes have similar values over land and ocean areas, with rainfall amplitudes between 1.5 and 2 times the mean. Phase differences between Fig. 11 (the diurnal cycle for all 3 years of data by PF type) and the total PF rainfall-gauge comparison in Fig. 2 over the Southeast US (encompassing JJA 1998 only) can be attributed to the limited sample in Fig. 2 compared with the 3 year sample in Fig. 11, and the separation of the diurnal cycle of rainfall into the three PF types in Fig. 11. The relative contribution of each PF type to the total rainfall diurnal cycle in each region (as in Fig. 11) determines the total rainfall diurnal cycle in that region.

PFs with ice scattering over land have higher diurnal amplitudes than over ocean, and peak in rainfall in the mid- to late afternoon. The only exception over ocean is within the low-precipitation areas of the Southern Hemisphere subtropical highs, where the sample size is low. Over the ocean, the magnitudes of the rainfall diurnal cycle for PFs with ice scattering are relatively uniform, but the phases vary significantly. The majority of boxes contain maxima from midnight to early morning hours, with a notable exception being the north Pacific north of 35°N containing a peak in the evening. PFs without ice scattering have a distinct oceanic maximum in the early
morning hours; with the amplitude roughly inverse to the climatological precipitation values (see Fig. 12 for the TRMM 3B43 precipitation during the same period). Over land, the magnitudes are consistently greater than those over high precipitation areas of the ocean, with a consistent peak around two times the mean timed in the early to mid-afternoon. While the results in Fig. 11 are roughly consistent with the bulk all-land and all-ocean values discussed previously, important regional variations exist which are a function of both bulk and local forcings (as shown in Fig. 3 over the Maritime Continent).

Regional Rainfall Diurnal Cycles

In order to expand on the results in the previous section, this section groups PFs observed in regions which likely contain similar climate forcings and thus, in bulk, similar forcings for the precipitating systems diurnal cycle. The regions used in this analysis appear in Fig. 12; the mean (December 1997-November 2000) 1° x 1° daily rainfall from the TRMM combined 3B43 algorithm is shaded for reference (note the 3B43 algorithm is IR-based with corrections mainly from gauge estimates over land; see Adler et al. 2000 for more details). Note in the figure that some regions contain over-land or ocean areas only, while some are mixed land and ocean regions.

Fig. 13 shows the diurnal cycle of total volumetric rainfall by region and PF type, plotted in polar coordinates and normalized to the daily mean rainfall for that feature type and region. The data are again binned into 2-hr blocks. Ocean regions are plotted in (a), (b), and (c); and land and mixed land and ocean regions are shown in (d), (e), and (f). In each figure, the global mean ocean and land amplitudes are plotted (thick line) in the corresponding figures.
Figure 12. Regional boundaries used in this study. Regions in plain type include only ocean areas, regions in boldface type include only land areas, while regions in italics include both land and ocean areas. The shading indicates the mean daily precipitation (mm day$^{-1}$) from the TRMM 3B43 combined precipitation algorithm (Adler et al. 2000).
Figure 13. The diurnal cycle of regional rainfall, with amplitude normalized to the regional mean value, plotted by PFs type. (a) PFs with MCSs over ocean, (b) PFs with ice scattering over ocean, (c) PFs without ice scattering over ocean, (d) PFs with MCSs over land, (e) PFs with ice scattering over land, and (f) PFs without ice scattering over land. Note the larger ranges on (e) and (f). The thin circles indicate amplitudes of 1.0 and 1.5 times the mean.
Figure 13. (continued)
For features with and without ice scattering over the ocean (b and c), the amplitude of the diurnal cycle is remarkably similar for all regions and the amplitude never varies by more than about 20% for any region. A peak for both types of features occurs in the early morning; PFs with ice scattering have a second, smaller peak in the afternoon. This second peak is especially prominent in the Central Pacific and SPCZ areas. This afternoon peak in the SPCZ is noted in the IR observations of Janowiak et al. (1994). This peak may suggest that the afternoon destabilization mechanism suggested by Chen and Houze (1997) may be occurring in calm, warm open ocean areas; however, the SPCZ hardly represents a calm ocean area like the west Pacific warm pool to the northwest. These small-to medium sized systems that start as individual cumulonimbi may grow, merge, and produce outflow boundaries that, later at night, form MCSs.

Oceanic MCSs’ diurnal cycle of rainfall have a higher amplitude by region than the other feature types. Every region (except the SPCZ) has a single peak between 0100 and 1100 LT. Interestingly, the SPCZ has a secondary peak around noon, which may again coincide with the Janowiak et al. (1994) observations. Some regions peak before 0600 LT (SPCZ, East Pacific, Indian Ocean, Central Pacific), whereas some peak after 0600 LT (Atlantic Ocean, Southwest Pacific, Northwest Pacific). Every region has below-mean rainfall amplitudes between 1500 LT and 2300 LT, illustrating the tropics-wide oceanic afternoon minimum in rainfall from MCSs. Note that the diurnal peak in rainfall from PFs without ice scattering occurs between 0100 and 0300 LT, from PFs with ice scattering between 0300 and 0500 LT, and MCSs for most regions between 0500 and 1100 LT. This highlights a slow upscale growth process
occurring overnight over the ocean. While PFs over the ocean are omnipresent in all regions, it appears that a growth process beginning with the smallest features around sunset may occur in all regions.

Over land regions, the diurnal amplitude of rainfall is, as shown before, much stronger for PFs with and without ice scattering (Fig. 13, e and f). Tropical and Subtropical Africa, and Tropical South America have the strongest amplitudes, with the African regions having the strongest amplitudes in the category with ice scattering (around 1500 LT), while Tropical South America has the highest peak in PFs without ice scattering (peaking earlier around 1500 LT). The Maritime Continent region (containing both land and ocean areas) diurnal cycle is comparable to the oceanic regions for non-MCS features, except for a small amplitude afternoon peak corresponding to the afternoon convective development over the islands (see Fig. 3). Interestingly, PFs without ice scattering amplitudes over the Southeast US/Mexico/Gulf of Mexico region appear very similar to the Maritime Continent’s, while features with ice scattering amplitudes appear more continental. This is due to the strong diurnal cycle over the Sierra Madre, Florida, and other land areas within the region.

MCS phases and amplitudes over land areas vary significantly. Subtropical regions generally contain peaks in the afternoon and before midnight (Subtropical Africa, Australia, India and Southeast Asia, and Southeast US/Mexico/Gulf of Mexico). Tropical South America and Tropical Africa have peaks between midnight and 0300 LT. India/Southeast Asia has a second peak around 0500 LT. The Maritime Continent’s peak occurs around 0700 LT, coincident with the peak in the SW Pacific region. Note the strong peak in Subtropical South American MCS rainfall around 0700 LT.
intense MCSs occur over Argentina and Uruguay preferentially in the hours around sunrise there during the warm season (Yorty 2001). While all continental regions have an afternoon (1300-1500 LT) peak in non-MCS features which decreases below mean values by sunset, only Subtropical areas have a corresponding maximum in MCS rainfall in the evening. Tropical areas’ MCS rainfall (Tropical South America and Africa) continues to well after midnight. Africa’s MCS rainfall rises to a constant level between 1900 and 0500 LT, while South American MCS rainfall has a peak around 0100 LT. These regional differences in the diurnal cycle over land implore further investigation into their controlling factors, whether they are related to surface, environmental, or topographic forcing (e.g., McCollum et al 2000).

Regional Diurnal Cycles of Convective Intensity

Figs. 14 and 15 plot the median values of the two parameters used to estimate the peak convective vigor of PFs presented in the previous section. Regional median minimum 85 GHz PCTs for PFs with MCSs and with ice scattering are plotted in Fig. 14 (features without ice scattering show no significant regional diurnal variation as shown by Fig. 8). With the sample size of PFs, the mean 90 percent confidence interval of the median minimum 85 GHz PCT for PFs with ice scattering, and with an MCS are ± 1.1 and 3.9 K, respectively. Over the ocean, PFs with ice scattering (Fig. 14b) have practically no significant diurnal and regional variation. MCSs over the ocean (Fig. 14a) have a slight tendency for more intense ice scattering in the early morning.

PFs with ice scattering over most land regions (Fig. 14d) have significantly depressed minimum 85 GHz PCTs in the afternoon, with mixed regions having only slight depressions in the afternoon and evening hours. Features containing MCSs (Fig.
Figure 14. The diurnal cycle of regional median minimum 85 GHZ PCTs of PFs by type. (a) PFs with MCSs over ocean, (b) PFs with ice scattering over ocean, (c) PFs with MCSs over land, (d) PFs with ice scattering over land.
Figure 14. (continued)
14c) also have a significant afternoon maximum in 85 GHz indicated convective intensity, with Tropical Africa and the Southeast US/Mexico/Gulf of Mexico regions contain some of the most intense ice scattering signatures from MCSs. Again, the Maritime Continent shows a more oceanic signature.

Similarly, median maximum heights of the 30 dBZ echo are plotted in Fig. 15 except PFs without ice scattering appear here (in c and f); the mean 90 percent confidence interval ± 0.02, 0.05, and 0.30 km for PFs without ice scattering, with ice scattering, and with MCSs. Again, oceanic features have little significant diurnal intensity variation (Fig. 15, a through c). While for 85 GHz comparisons, PFs without ice scattering had insignificant variations among oceanic regions, here the Southwest Pacific region has the most intense radar signature, while the Central Pacific has the least. These differences become less considering the other two feature types (Fig. 15, a and b). There is a slight tendency for features with MCSs (a) to have roughly 500 m higher median 30 dBZ heights in the predawn hours over the ocean.

Over land (Fig. 15 d through f), all three types of features have a significant diurnal intensity maximum in the afternoon. The Maritime Continent region again is an obvious outlier here, although there is a slight perturbation in 30 dBZ heights in the afternoon in non-MCS features corresponding with the afternoon development of convection over the islands (see Fig. 2). The timing of the maximum is consistent among all land regions and all feature types, as well as the prominence of Tropical Africa and Australia having the most intense and weakest radar profiles according to all three feature types, respectively.
Figure 15. The diurnal cycle of regional median maximum 30 dBZ echo top heights of PFs by type. (a) PFs with MCSs over ocean, (b) PFs with ice scattering over ocean, (c) PFs without ice scattering over ocean, (d) PFs with MCSs over land, (3) PFs with ice scattering over land, and (e) PFs without ice scattering over land. The legends at right correspond to the row of figures to their left.
Figure 15. (continued)
Summary

The diurnal cycle of remotely sensed rainfall and convective intensity is analyzed from 3 years of data from the TRMM PR and TMI. The PR’s 2A25 radar reflectivity-rain rate relationship offers more direct remote-sensing estimates of near surface rainfall than other methods (IR or microwave brightness temperatures), offering quantitative instantaneous estimates of surface rainfall amount, convective-stratiform portioning, and yielding proxies for convective intensity. Observations from the PR and TMI between ±36° latitude are collocated, and grouped into individual storms, or so called precipitation features (PFs) larger than 75 km² in size using the algorithm outlined in Nesbitt et al. (2000). The algorithm classifies the storm into three types: MCSs, features with TMI 85 GHz PCT ≤ 250 K not meeting MCS size or intensity criteria (convective clouds with significant optical depths of ice aloft), and features without 85 GHz PCT ≤ 250 K (small convective features or “warm rain”). Diurnal composites of the rainfall and other properties of the PFs by storm type yield a tool to examine their daily variation. Sampling from the low-earth orbiting TRMM satellite (with its 215 km PR swath) must be taken into account, in this study only 3-year composites over all tropical ocean and land areas are examined, regional investigations are made at no less than 10° grids for 3 years. These composites are used to examine the large-scale bulk characteristics of the tropical diurnal cycle.

Rainfall over the oceans has a significant diurnal cycle (varying by 30%) that peaks in the early morning to predawn hours, with a minimum in the late afternoon. This rainfall maximum is due to increased rainfall contributions from MCSs; diurnal rainfall variations from non-MCS features remain minimal. These trends are similar
among all the ocean regions considered in this study. The increased number of MCSs observed in the early morning hours combines with slightly increasing median areas, leading to this rainfall peak.

Total conditional rain rates, convective and stratiform portioning, and rain rates remain constant over ocean, conveying that this predawn rainfall maximum is not due to increased rain rates within the systems sampled. Thus, this leads the authors to clarify previous theories on diurnal cycle mechanisms that may suggest that rain rates are heavier during the observed predawn maximum of oceanic rainfall. This study sees little enhancement in the observed convective intensity and conditional rain rates that correspond with the observed early morning maximum in rainfall (in agreement with the results of Dai 2001). The increased number of systems observed during the predawn hours suggest that over the ocean, the nocturnal environment is simply more favorable for cloud systems to grow to become MCSs, or for MCSs to live longer (snapshots from TRMM do not allow the direct observations of system life cycle).

Over land, all feature types contribute to an afternoon maximum in precipitation (which has a magnitude variation of 125%), but MCS rainfall peaks in the early morning. The number of systems, conditional rainfall rates, and convective intensities of features without and with ice scattering respond strongly to afternoon heating. An increase in conditional rain rates in non-MCS systems, in particular, corresponds to an afternoon peak in convective rain fraction. This result differs from the rain gauge analysis of Dai et al. (1999); this is attributed to different areas of study and sampling differences by instantaneous (this study) versus hourly rain measurements (used in the Dai et al. study). MCSs over land also see an increase in conditional rain rates and
convective intensities in the afternoon; however their persistence and increasing areas throughout the nighttime lead to a near-midnight maximum in MCS rainfall (Laing and Fritsch 1997). While the timing of rainfall from features with and without ice scattering was in phase among regions, rainfall amplitudes varied considerably. Both the timing and amplitude of MCS regional rainfall also varies significantly, with subtropical (30°-35° latitude) MCS rainfall peaks during the evening; tropical areas MCS rainfall peaks tend to be after midnight. These differences are likely due to the varying dynamical and thermodynamical environments in which these storms form.

The mechanisms of the rainfall peak associated with over land afternoon instability are well understood and observed. However, the diurnal cycle of rainfall associated with MCSs remains poorly understood and modeled. This results from our incomplete understanding of land surface fluxes, effects of nearby topography, and their relation to convective processes.

The eventual goal of this research is to provide a database that may facilitate the evaluation of cloud-resolving models (CRMs) on a statistical basis as well as the performance of global circulation models (GCMs), such that our understanding of the diurnal cycle (and the climate system as a whole) may be improved. Matching the sampling of TRMM with that of numerical model simulations will be a major challenge of this effort. The accumulation of additional data from TRMM and the planned Global Precipitation Mission (GPM) will allow a more comprehensive regional and seasonal remote-sensing evaluation of rainfall and convective intensity.
CHAPTER 3
AN EVALUATION OF TROPICAL RAINFALL MEASURING MISSION
RADAR AND PASSIVE MICROWAVE RAINFALL ESTIMATES
USING PRECIPITATION FEATURES

Introduction

Precipitation processes play a fundamental role in many aspects of the global climate system. Aside from direct impacts such as determining the local hydrology over land or the salinity of the ocean, the location and intensity of precipitation significantly affects the local and global radiative forcing, general circulation, and atmospheric chemistry (IPCC, 2001). The globally averaged precipitation rate of approximately 2.7 mm dy⁻¹ corresponds to a globally averaged vertically-averaged forcing of +78 W m⁻² due to latent heating. However, rainfall contains extreme spatial and temporal variability, such that local rain rates and vertically integrated heating rates vary locally by several orders of magnitude. The magnitude of these regional heating rates is such that they have significant impacts on the global circulation (i.e., the structure of the Walker Circulation). Understanding the horizontal morphology of rainfall patterns and knowing the bulk and regional characteristics of the heating profiles associated with precipitation’s vertical structure are crucial in representing the details of the global circulation (e.g., Hartmann et al. 1984). Thus, quantifying the spatial and temporal variability of precipitation is crucial in the understanding of many
physical components of the Earth-Atmosphere System. Shortfalls in our observations and modeling of precipitation processes hamper our ability to model the current variability of the atmosphere, and our ability to predict the impacts of climate change.

Many techniques have been used to estimate the spatial and temporal variability of precipitation. However, sources of error in these estimates often stem from this very variability in both space and time, or, in the case of the remote sensing of rainfall, physical indirectness of the inversion technique used to estimate rainfall. These difficulties are exacerbated in the Tropics and mid-latitude warm seasons (hereafter referred to as simply the “Tropics”), where rainfall often occurs in a mixed convective/stratiform mode. Differences in modal conditional rain rates (defined as rain rates when it is raining), particle size distributions (PSDs, both liquid and frozen), number concentrations, and densities, as well as vertical profiles of heating associated with convective and stratiform precipitation are significant; the inability to differentiate these rainfall modes causes significant uncertainties in our understanding of precipitation. Accurate remote sensing rainfall algorithms must account for the varying radiative signatures of these modes of rainfall, otherwise the use of them will inevitably lead to errors in quantifying global climate feedbacks of rainfall systems.

In a rainfall-by-system type framework, the largest and most easily recognizable mode (from a satellite image) is the Mesoscale Convective System (MCS, Zipser 1982, defined by remote remote sensing criteria by Houze 1993, Mohr and Zipser 1996, and Nesbitt et al. 2000). The classical conceptual diagram of a MCS (e.g., Biggerstaff and Houze 1991) depicts a deep convective feature containing a leading line of convection and a trailing stratiform rain region. While these features have been found to contribute
more than 50% of the total rainfall in a given tropical rainy region (Rickenbach et al. 1998, Nesbitt et al. 2000), studies by ground-based radar (Parker and Johnson 2000) indicate that these systems are structured like the classic conceptual structure only about 40% of the time, depending strongly on location and meteorological regime. Convection is often embedded within the stratiform rain areas. This can make the separation of convective and stratiform rainfall difficult from a remote sensing point of view (Biggerstaff and Listemaa 1999); with important consequences due to differing convective and stratiform modal conditional rain rates, and vertical profiles of hydrometeor type, density, and number concentration, as well as heating rates. Quantifying the rainfall contribution from MCSs, which contribute significantly to the regional rainfall and heating budgets, is crucial to the understanding the climate system as a whole.

Significant rainfall occurs from systems not meeting MCS size or intensity criteria. In fact, many of the rainiest places in the world rarely see such organized systems. Rainfall modes from small, warm cumulus clouds through individual cumulonimbi to sub-MCS-sized cumulonimbus cloud clusters not meeting MCS criteria contribute significantly to the rainfall in many areas. The microphysical and heating profiles of these systems likely differ significantly from those of MCSs; local and bulk contributions from these systems cannot be neglected if we are to understand the global climate (Short and Nakamura 2000). From a remote sensing standpoint, however, these small to medium sized systems often present an additional challenge in their quantification due to their size or radiative signal being too small (beam filling) or weak.
(lack of instrument sensitivity) to yield a signal in a given relatively large satellite footprint.

The Tropical Rainfall Measuring Mission (TRMM) satellite was launched in November 1997 to study the variability of rainfall in the Tropics (Simpson et al. 1988) with a collocated suite of instruments designed to provide both radar reflectivity profiles and high-resolution passive microwave measurements. The platform allows quantitative, collocated comparisons of rain estimates from both types of sensors. The TRMM instruments (see Kummerow et al. 1998 for a complete description) include the first quantitative spaceborne radar, the 14.8 GHz (2.2cm) Precipitation Radar (PR) and the TRMM Microwave Imager (TMI), providing brightness temperature measurements at nine channels between 10 and 85 GHz. Observations from these two sensors, since launch, have provided the most comprehensive dataset to date allowing the characterization of the radar and ice scattering properties of precipitating systems, as well as precipitation estimates. In addition, the sensors’ high resolution, extensive geographic coverage (Tropics-wide between ±35° latitude), and nonsunsynchronous orbital sampling (precessing through the diurnal cycle in roughly 45 days) has generated a dataset facilitating the investigation of the climatic properties of precipitating systems and variability of rainfall throughout the tropics.

Kummerow et al. (2001) report that estimates of rainfall from the TRMM TMI 2A12 version 5 rainfall algorithm exceed those from the PR 2A25 version 5 algorithm by 20% and 23% over land and ocean, respectively. These TMI-PR differences are due many factors including differing swaths of the instruments leading to different sampling, differing physics of the retrieval techniques (active vs. passive microwave
retrievals and their inherent assumptions), and some artifacts in the estimates. While identifying the global, land-ocean, and zonally averaged differences in rainfall estimates can be useful to diagnose the algorithms’ differences, important meridional, regional, and seasonal variations in the modes of rainfall observed can mask some of the true causal mechanisms of the divergence of the rain estimates (Ferraro et al. 1998). These differences in regional rainfall properties can be examined by looking at the properties of the rainfall systems occurring in that region, identifying modes of rainfall that occur that are (1) responsible for a significant fraction of the rainfall in a given region, (2) easily classifiable by existing remote sensing techniques, (3) climatically important for their characteristic heating and divergence profiles, and (4) responsible for a unique but identifiable contribution to the differences in the rainfall estimates because of their characteristic hydrometeor profiles. In this vein, the classification of storms within the TRMM dataset is performed in hopes of using our added understanding of the modal properties of these systems to evaluate rainfall estimates in regions where they occur.

To better quantify the role of various modes of rainfall in the climate system, the TRMM precipitation feature (PF) algorithm has been devised to identify and classify individual systems within the PR swath (Nesbitt et al. 2000). In the algorithm, the PR and TMI observations (and rainfall estimates) are collocated and used to quantify the rainfall and intensity of precipitation features classified to be representative of important modes of tropical rainfall. This study uses the precipitation feature algorithm to (1) examine the climatic-scale differences in the PR and TMI estimates, comparing them to other in situ and satellite estimates, and (2) examine a shorter term dataset of
matched feature-by-feature estimates of PR and TMI rainfall in a global sense to identify regional and system-type biases. Note that “climatic-scale” is defined as spatial scales larger than $10^4$ km$^2$ (1° latitude/longitude) and temporal scales larger than seasonal (3-month averages). This falls within the definition of Arkin and Ardanuy (1989), who define climatic scale with similar spatial scales, but with temporal scales extending down to 5-day averages. On both climatic and system-by-system scales, ancillary observations from TRMM and meteorological understanding of regional and system-type modes of rainfall are used to decipher the differences in the precipitating systems that cause the algorithms to diverge from each other or other rainfall estimates.

This analysis is motivated by the following tenets:

1. If long-term regional biases exist in the PR and TMI estimates with respect to each other, to gauges and to other estimates then differences can be linked to inappropriate algorithm assumptions, artifacts, or sampling uncertainties in that region and corrections may be applied;

2. If biases can be identified on an instantaneous system type-by-system type basis, then the physical assumptions (i.e., the brightness temperature-rain rate relationship, identification of rain type within the system, drop size distributions, beam filling corrections, etc.) of future rain algorithms may be implemented using a storm-type classification approach.

The analysis presented herein will focus on comparisons over land where TMI estimates rely on the ice scattering channels alone and the rainfall relationship is inherently empirical in contrast to measurements over the ocean (where a more physical approach using all 9 TMI channels can be used). In addition, over-land comparisons
afford the use of gauge networks, which, in regions where they exist, can provide useful validation data of long-term rainfall averages.

Rainfall Estimation from the TRMM Satellite

The TRMM mission produces three rainfall estimates, the TMI 2A12 passive microwave algorithm (Kummerow et al. 1996, Kummerow et al. 1998, Kummerow et al. 2001), the PR 2A25 radar algorithm (Iguchi and Meneghini 1994; Iguchi et al. 2000), and the combined PR-TMI 2B31 algorithm (Smith et al. 1997, Haddad et al. 1997). The former two algorithms are examined in this study due to their more basic physical assumptions, use of a single instrument, and their wide use. Hereafter, the 2A12 (2A25) algorithm will be referred to as the TMI (PR) rainfall estimates. This section will discuss the instruments used to make the estimates, the details of the algorithms, and differences in those algorithms that may lead to differences in the rain estimates produced by them.

The TMI and Rain Estimation

The TMI is a nine-channel, dual polarization elliptically-scanning passive microwave radiometer which views the earth at a 52.8° incidence angle (see Kummerow et al. 1998 for a complete description of the TMI). It has a swath width of 759 and 873 km corresponding to pre- and postboost conditions. (The TRMM satellite was boosted from a nominal altitude of 350 km to 402.5 km during August 2001 for fuel savings. This “boost” resulted in a decrease in the areal resolution of the sensors by roughly 30 percent.) The sensor measures horizontally and vertically polarized brightness temperatures at 10.65, 19.35, 37.0, and 85.5 GHz, with vertical polarization...
at 21.3 GHz\(^5\). Effective fields of view vary from \(63 \times 37\) and \(72 \times 43\) km at 10 GHz to \(7 \times 5\) and \(8 \times 6\) km at 85 GHz pre- and postboost conditions, respectively. The TMI scans roughly every 14 km along its nadir point, leading to along-track oversampling at all channels except at 85 GHz, which undersamples by approximately 7 km between each scan. The TMI version 5 products are calibrated to both internal checks (including looks at the cosmic background radiation) as well as a comparison of coincident brightness temperature distributions from three satellites carrying the Special Sensor Microwave Imager (SSM/I) instrument, which have intercalibration biases on the order 0.5 K.

Rain estimation techniques using passive microwave brightness temperature observations have existed for decades. These techniques can be broken down into two types: emission-based and scattering-based. Emission techniques will be mentioned briefly here since the focus of this paper is on over-land comparisons; however, these methods form the basis for current over-ocean retrievals. Since the ocean surface is radiatively cold and its emissivity is nearly uniform at microwave frequencies, thermal emission from liquid hydrometeors and cloud liquid water increase upwelling brightness temperatures, especially at lower frequencies (Wilheit et al. 1977, 1991; Prabhakara et al. 1992). Emission techniques may not be used over land surfaces because of land’s high and nonuniform emissivity (which typically is about 0.9 compared to the over-ocean value of 0.6). The amount of thermal emission at these frequencies for small drops (< 100 \(\mu\)m) is proportional to the sum of the volume of drops within the layer (Wilheit et al. 1977). For drops > 100 \(\mu\)m, this relationship is

\(^5\) Hereafter, TMI channels will be referred to as their first two digits (i.e., 85.5 GHz is the 85 GHz channel).
somewhat complicated by resonance effects and droplet scattering within the rain layer, however the absorption coefficient is still an order of magnitude greater than the scattering coefficient at these low frequencies (Stephens 1994). This fact allows retrievals to be insensitive to the details of the drop size distribution (DSD) because the absorption coefficient is proportional to the mass of the drops in the emitting layer, which is a major advantage over radar-based retrievals. In algorithms of this type however, assumptions of the height of the freezing level (Wilheit et al. 1977, Harris et al. 2000) and the effects of nonuniform beam filling (Ha and North 1993) must be made, errors can add bias and random error to rain rate estimates. Additional complications come from emission masking by overlying ice scattering layers (Liu and Curry 1999) and the radiative effects of the bright band (Bauer et al. 1999, Olson et al. 2000).

Scattering-based techniques of rain estimation at 85 GHz rely on the relation between optical depths of precipitation-sized ice particles and surface rainfall. Brightness temperature depressions at 85 GHz are caused by scattering due to ice particles greater than roughly 100 µm in size (Vivekanandan et al. 1991), reaching peak extinction efficiencies in the Mie scattering regime with particle sizes around 4 mm (Ferraro and Marks 1995). While not as direct of a physical measurement of rain as emission techniques, ice scattering techniques are applicable over both land and ocean surfaces since the measurement is insensitive to the background properties at rain rates greater than a few mm hr⁻¹ (Vivekanandan et al. 1991). Depending on the rainfall regime (i.e., one dominated by warm rain), however, this threshold may cause a lack of sensitivity to a significant portion of actual rainfall.
Despite the ice scattering technique’s applicability over land and ocean surfaces, complexities in the radiative transfer and a lack of measurement constraints (i.e., few frequencies available) do not allow a physical retrieval algorithm to be used like in emission algorithms. The volume scattering coefficient at a given frequency and polarization depends on the phase, density, size distribution, shape, and orientation of the ice particles (Mugnai et al. 1990, Vivekanandan et al. 1991, Kummerow et al. 2001), none of which are known to great certainty within a given satellite footprint. In addition, the cloud scene within a given satellite footprint adds complexity due to its inhomogeneity due to multiple scattering (Roberti et al. 1994), and cloud tilt with respect to the viewing angle of the instrument (Hong et al. 2000). The only purely scattering channel often available is at 85 GHz, which does not sufficiently constrain rain estimation methods that rely on statistical convergence with modeled hydrometeor profiles (Kummerow et al. 2001). Thus, most ice scattering rainfall retrieval methods are left to use empirical methods in determining their brightness temperature-rain rate relationships (Spencer et al. 1989, Ferraro and Marks 1995). These relationships are often derived from a limited sample of observations in a given region where validation networks exist (e.g., ground based-radar networks), significant deviations in the cloud system properties likely exist globally, which is liable to bias scattering rainfall estimates. This study will examine these possible biases in the context of global and regional rain gauge networks and PR observations.

The TMI rain algorithm (historically known as the Goddard Profiling Algorithm or GPROF, Kummerow et al. 1996, Kummerow et al. 2001) uses statistical techniques to match the nine observed brightness temperatures from a pixel with those from a
database of simulated hydrometeor profiles from a cloud resolving model coupled with a microwave radiative transfer model. The current version of the algorithm uses five simulations of convective systems for its hydrometeor database: two initialized with initial conditions from the Tropical Ocean and Global Atmosphere Coupled Ocean-Atmosphere Response Experiment (TOGA COARE), one from the Global Atmospheric Research Program (GARP) Atlantic Tropical Experiment (GATE), one from the Cooperative Huntsville Meteorological Experiment (COHMEX), and a hurricane simulation. The former three simulations were performed using the Goddard Cumulus Ensemble (GCE) Model (Tao and Simpson 1993), while the University of Wisconsin Nonhydrostatic Modeling System (UW-NMS, Tripoli 1992) performed the latter two. The GCE and UW-NMS modeling systems differ in their treatment of dynamics and microphysics; however, both used parameterized bulk microphysics schemes. This selection of cloud simulations contains four oceanic-type systems and only one continental-type system (the COHMEX simulation), however the COHMEX case was sampled more frequently to include more continental-type hydrometeor profiles. The hydrometeor profiles output from the model are then passed through the plane parallel microwave radiative transfer model outlined in Kummerow (1993). One source of uncertainty in retrieval techniques of this sort is the representativeness of the simulated cloud profiles to clouds in nature. The use of as many varied simulations as possible is desirable, but this is offset by the need for meaningful and computationally fast statistical convergence in the selection of a representative hydrometeor profile. The use of a limited number of profiles differing from those occurring in nature is major source
of uncertainty in the retrievals. This issue will be addressed in version 6 of the algorithm (McCollum and Ferraro 2002).

The algorithm has different methods of matching the observed brightness temperatures with the model database over ocean and land. Over ocean, the usefulness of both emission and scattering techniques allows the efficient use of a Bayesian method to select hydrometeor profiles in the database (Kummerow et al. 2001). In addition, a convective-stratiform separation algorithm is used over ocean (see Olson et al. 2001 for details).

Over land, however, only scattering signatures are available for rain estimation, which yields too little information to use a Bayesian hydrometeor selection technique in GPROF (Kummerow et al. 2001). In version 5 of the TMI algorithm, it was decided to selectively match the cloud model database with the ice scattering-rain rate algorithm created for operational use by the National Oceanic and Atmospheric Administration (NOAA) National Environmental Satellite, Data and Information Service (NESDIS). The algorithm, outlined in Ferraro (1997), was originally developed for use with SSM/I data and incorporates a surface screening method, which attempts to remove scattering effects from snow cover and other low emissivity surfaces. The NESDIS algorithm uses a scattering index (SI) approach developed by Grody (1991) where SI is empirically calculated based on the 19, 22, and 85 GHz vertically polarized brightness temperatures ($T_b$ s):

$$SI \text{[K]} = 451.9 - 0.44T_{b_{19}} - 1.775T_{b_{22}} + 0.00575T_{b_{22}}^2 - T_{b_{85}}.$$

The 19 and 22 GHz $T_b$s are used to remove effects of nonuniform surface emissivity. A SI-rain rate algorithm was calibrated (Ferraro and Marks 1995) using rain
estimates from matched low-level radar reflectivity scans from the eastern US, Japan, and United Kingdom. The composite relationship was derived as the following:

\[ RR \text{ [mm hr}^{-1}\text{]} = 0.00513 S_I^{1.9468}. \]

The surface rain rates from the GPROF hydrometeor database matching the NESDIS empirical SI-rain rate relationship are selected for use in the version 5 algorithm. Thirty GPROF profiles were selected which matched the NESDIS algorithm, and these 30 rain rates are the only available for Bayesian selection from the profile database. This results in the TMI algorithm only having discrete rain rates available for assignment to the observed brightness temperatures, not a continuous spectrum of rain rates as the above relations suggest. While the algorithm is applied globally over land, its calibration database relies on data collected from midlatitude areas. This fact is a likely a source of uncertainty in the TMI over-land rainfall retrievals when they are applied to rainfall systems globally. The future version 6 of the TMI algorithm will use collocated PR data as its source of a brightness temperature-rain rate relationship, a continuous rain rate histogram derived from TMI-PR rain rate match-ups, as well as a prototype microwave-only convective-stratiform separation (McCollum and Ferraro 2002).

Low emissivity land surfaces (i.e., snow cover, surface water, lakes) appear radiometrically similar to rain signatures at 85 GHz. Effects of surface scattering artifacts (i.e., snow cover, inland lakes) and emissivity differences at coastlines present complications in scattering rainfall algorithms (Grody et al. 1991, Ferraro et al. 1998, Kummerow et al. 2001). Surface properties are highly spatially and temporally inhomogeneous, making the creation of artifact screening procedures difficult. In
version 5 (and the planned version 6), a global threshold of $T_{b_{21V}} < 262$ K is used for identifying snow or ice surfaces; no rain rate is derived in areas meeting this threshold. This screen may also be triggered by other radiometrically cold surfaces caused by high soil moisture contents, for example, introducing systematic biases in regions where this occurs (McCollum and Ferraro 2002). Coastline pixels in the TMI algorithm are treated as “land” as well, and the surface screening technique may complicate retrievals near coasts. The development of better microwave screening techniques remains a goal for future research; this study will allow identification of locations where surface screening problems may occur on a climate scale.

The PR and Rain Estimation

The PR is the first spaceborne rain radar. Due to engineering constraints, spaceborne radar capabilities are limited in power and wavelength selection compared to their ground radar counterparts, the former condition leading to a high minimum detectable signal (~ 17 dBZ for the PR), and the latter condition leading to significant attenuation by precipitation at its transmitting frequency (wavelength) of 13.8 GHz (2.2 cm). However, the PR’s great advantages are its tropics-wide coverage in regions that are devoid of ground-based radar coverage, and its down-looking scan geometry that allows retrievals close to the surface, and excellent vertical resolution when compared to ground-based scanning radar. The PR’s horizontal resolution is $4.3 \times 4.3$ and $4.9 \times 4.9$ km at nadir for pre- and postboost conditions, while its vertical resolution is 250 m at nadir, decreasing to effectively 1.5 km at the swath’s edge. See Kummerow et al. 1998 for a complete description of the PR algorithm. The PR scans cross-track through 49 rays over a 220 km swath; at its edge, the PR has a $17^\circ$ off-nadir incidence angle.
with the surface. The PR’s calibration has been extremely stable over its lifetime, varying within ±0.2 dB with respect to both transmit and received power as well as calibration with ground-based sensors (Kummerow et al. 2000).

The process of inverting the PR’s measured reflectivity to attenuation-corrected equivalent reflectivity factor \( Z_e \) and rain rate is accomplished by the 2A25 algorithm, which is detailed in Iguchi et al. (2000). Measured heights of the bright band and climatological surface temperature data are used to estimate the heights of liquid, mixed-phase, and frozen hydrometeors using the 2A23 convective-stratiform separation algorithm. The convective-stratiform separation algorithm uses reflectivity gradients in both the horizontal and vertical to identify rain type. The horizontal method is similar to other techniques such as the Steiner et al. (1995) technique whereby strong reflectivity gradients in the horizontal signify convective echoes. In addition, the PR’s high resolution in the vertical allows identification of the radar bright band caused by melting aggregates in the stratiform region. Both of these techniques are used to classify rain types with a prescribed confidence (whether the horizontal and/or vertical criteria were met). There is some ambiguity in any classification scheme of this type (Biggerstaff and Listemaa 2000), and evaluation of the PR’s classification scheme’s error characteristics remain a topic of future work.

Total path attenuation estimates are taken from algorithm 2A21, which uses the difference in ground return from rainy and nonrainy regions to estimate the power attenuated by the hydrometeors in the beam. In addition, specific attenuation \( k \) is estimated using a Hitschfeld-Bordan method (Iguchi and Meneghini 1994), whereby the attenuation is estimated as a power law function of the measured reflectivity itself.
The former of the two methods are more reliable in heavy rain rates because there is a large signal difference in the surface return and the Hitschfeld-Bordan technique may yield a divergent profile solution, the opposite is true in light rain rates. In calculating the “true” profile of $Z_e$, differences in the two methods of attenuation correction are attributed to a bad initial guess in the DSD, such that the coefficients in the Hitschfeld-Bordan method are adjusted to make the two methods consistent. The initial $k - Z_e$ and $Z_e - R$ relationships are then defined. The effects of nonuniform beam filling are then taken into account, whereby the horizontal variability of total path attenuation for the eight pixels surrounding each pixel is calculated, and set to be proportional to the within-pixel nonuniformity. The modified path attenuation is then used to adjust the $Z_e$ profile within the pixel. Using the estimate of nonuniformity, the DSD model is adjusted to be consistent with the $k - Z_e$ relationship, and this along with the $2A23$ convective-stratiform classification, estimated height of the freezing level, storm height, hydrometeor phase, temperature, and terminal velocity information, are used to calculate the coefficients $a$ and $b$ in the $Z_e - R$ relationship, where

$$R = aZ_e^b.$$  

The use of single-frequency, nonpolarimetric radar requires an assumption of the DSD, and the estimate of rain rate from reflectivity is highly sensitive to this assumption because reflectivity measurements are a function of $\sum D^6$. Regional and storm- and rain-type variations in DSD have been commonly observed, causing a significant source of uncertainty in radar rain estimates (e.g., Atlas et al. 1999; Atlas et al. 2000; Rosenfeld and Ulrich 2002). In addition, the PR’s narrow swath limits its
sampling by a factor of 3.5 compared with the TMI, resulting in greater sampling uncertainties in deriving climate-scale rain estimates. However, the PR’s active sensing technique yields many advantages with respect to the TMI: ability to observe rain at finer resolution, more easily discriminate rain type (and their modal DSDs, vertical profiles, and rain rates), and more directly estimate over-land near surface rain rates (as opposed to the less-direct ice scattering signatures measured by the radiometer) offsets DSD assumption and sampling errors in making it a more direct measurement of near surface rainfall. With these factors in mind, this study seeks to evaluate and compare the TMI and PR rainfall estimates using the approach outlined above.

Data and Methods

The comparisons of the data on both the climate scale and feature-by-feature sense in this study use data from two different time periods (December 1997-November 2001 unless otherwise noted versus March through August 2002) and two versions of the PF algorithm (see below). All TRMM products used are version 5 of the algorithms. Note that TRMM data before August 2002 corresponds with preboost conditions (and higher spatial resolution), while those collected afterwards are from the postboost period (with 15% lower spatial resolution).

The long-term data are used in this study to compare gridded rainfall estimates from the PR and TMI algorithm with those from other estimates. The PR and TMI datasets used in long term averages are from the algorithm 3G68⁶ 0.5° × 0.5° hourly gridded rainfall products, which are derived from the raw PR and TMI estimates. In

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⁶ 3G68 products, created at NASA Goddard Space Flight Center (GSFC) by the TRMM Science Data and Information System (TSDIS); information is available at http://tsdis.gsfc.nasa.gov/trmmopen/.
addition, the merged TRMM 3B43 product is presented in the seasonal time series; this data product incorporates data from the PR and TMI above, and also other microwave, infrared, and gauge rainfall data. The reader is referred to Adler et al. (2000) for a complete description of 3B43. It is worth noting, however, that over land areas the 3B43 product is heavily weighted by the GPCC gauge analysis discussed below.

Monthly global rain gauge data are from the Global Precipitation Climatology Centre (GPCC) “Monitoring Product” (GPCC 2002). The analysis is performed on a 1° × 1° grid using an objective technique presented in Rudolf (1993). The data source is quality-controlled globally exchanged synoptic weather reports (SYNOP) and monthly climate reports (CLIMAT) from roughly 6,000 to 7,000 stations. Fig. 16 shows the mean number of gauges per month in each 1° grid box in the tropics for the period December 1997-November 2001. Note that gauge coverage is concentrated in developed countries, which leaves a dearth of gauges in the low latitude areas. Only about 10% of the globe’s 1° grid boxes within 40° of the equator have at least one gauge report, while about 45% of the land areas within this latitude belt have gauges. Most of those gauges are far from the equator, however. This presents a challenge in using such gauge analyses for satellite validation. In addition to gauge’s tendency to underestimate rainfall (e.g., in high winds), it has been found necessary to have at least five gauges in a 2.5° × 2.5° grid box to reduce sampling errors to within 10% (Legates and Willmott 1990). This condition is met in only 8.4% of the over land grid boxes in the GPCC dataset regridded to 2.5° × 2.5° resolution during the 4-year period described above.
Figure 16. Mean number of GPCC gauge stations in each 1° × 1° grid box.
Daily rain gauge data over the US are from the real-time gridded 0.25° × 0.25° analysis performed by the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC). Data are obtained from the NOAA River Forecast Centers, which collect data from about 5000 stations per day, and the CDC Climate Anomaly Data Base, which collects several hundred stations per day. Automated quality control procedures include a duplicate station check, a standard deviation check against climatology, and a check against coincident ground-based radar observations for spurious zeroes in the data. Daily 1° × 1° gridded Geostationary Operational Environmental Satellite (GOES) Precipitation Index (GPI, Arkin and Meisner 1987) rain estimates were also obtained from the CPC. The GPI is an indirect estimate, since its rainfall estimates are based on the time fractional coverage of cold cloud top temperatures within a given area. Specifically the GPI rain rates are calculated by:

\[
GPI \ [\text{mm hr}^{-1}] = F \cdot R \cdot T
\]

where \( F \) is the fractional coverage of 10.7 \( \mu \)m channel pixels with a \( T_b < 235 \) K, \( R \) is an empirical constant of 3 mm hr\(^{-1}\), and time is the number of hours over which the fraction \( F \) was compiled. The GPI has been shown to be reliable in a tropical or subtropical atmosphere, with a major advantage of near-continuous sampling; however, during cold seasons it tends to overestimate due to nonprecipitating but radiometrically cold upper-level clouds, and the predominance of lighter stratiform rainfall.

For the long term-estimate comparisons, the classification of rainfall into precipitation features for the period December 1997-November 2000 has been performed using the algorithm described in Nesbitt et al. (2000), whereby PR and TMI data are collocated within the 215-km wide PR swath to identify contiguous areas of PR
rainfall and TMI 85-GHz ice scattering. In the collocation procedure, the TMI data are shifted one scan (~14 km) towards from the satellite to account for the “parallax” between the two instruments caused by the PR and TMI difference in viewing angles (the ice scattering signature aloft is “apparently” shifted towards the satellite due to the TMI’s 53° viewing angle). A nearest-neighbor matching technique is then applied to match the two datasets, meaning that every PR pixel was matched with the nearest TMI pixel, with the PR used as the base grid. Since the TMI data are geolocated at the surface, the TMI scans were shifted 1 scan (~14 km) away from the satellite in the along-track direction to match the oblique sampling volume of the TMI in the ice region (~10 km altitude) with the downward looking PR. In Nesbitt et al. (2000) and for the long term comparisons in this study, PF areas were required to be at least four PR pixels in size (~75 km²) and to contain either PR near-surface reflectivities ≥ 20 dBZ or 85 GHz PCT ≤ 250 K. Since the ocean is generally smooth, its emissivity is higher at horizontal polarization than at vertical polarization in the microwave. Scattering from intervening hydrometeors is polarized less than ocean surfaces, so this information can be used to remove radiometrically cold water backgrounds. PCT (Spencer et al. 1989) is calculated in order to remove these effects from the vertically and horizontally polarized 85 GHz TMI channels (\( T_{\text{b\mu}} \) and \( T_{\text{b\nu}} \), respectively):

\[
PCT = \frac{(\beta T_{\text{b\mu}} - T_{\text{b\nu}})}{(\beta - 1)},
\]

where \( \beta \) is set to 0.45.

For the feature-by-feature comparisons using data from March-August 2002, the PR and TMI datasets have been merged using the same technique outlined in Nesbitt et al. (2000). However, PFs are identified as any areas within the PR swath with TMI or
PR rain rate $> 0$ mm hr$^{-1}$, with no minimum pixel area or 85 GHz PCT threshold applied. Most pixels with 85 GHz PCT $< 250$ K, in the absence of surface artifacts, should have a nonzero rain rate, so this definition is, for the most part, inclusive of the Nesbitt et al. (2000) definition. This change in the precipitation feature definition results in the inclusion of 19% more raining pixels (those between the PR minimum detectable signal of 17 and 20 dBZ and having a size between 1 and 4 pixels); about 4% of the total PR near-surface rainfall is added. For each PF in this definition, the rain estimates for the PR and TMI are matched on a feature-by-feature basis. This isolates sampling differences and allows direct storm-type comparisons between the PR and TMI estimates using the criteria below. Both definitions of PFs are classified by their radar and ice scattering properties using the same three categories (see Fig. 1 for a schematic).

- **PF without ice scattering** (no pixels containing PCT $\leq 250$ K at 85 GHz). These are likely to be “warm rain” features too shallow or those too small to contain significant ice scattering at TMI resolution.

- **PF with ice scattering** (at least one pixel with 85 GHz PCT $\leq 250$ K). These are features with significant optical depths of ice aloft, but are not large or intense enough to meet the MCS category.

- **PF with a MCS** (PF contains at least 2000 km$^2$ of contiguous area with 85 GHz PCT $\leq 250$ K and 185 km$^2 \leq 225$ K). These are defined to ensure a large convective system analogous to the Mohr and Zipser (1996) and Houze (1993) ice scattering and radar MCS definitions, respectively.
The three feature classifications are noted as NI, WI, and MCS for features without ice scattering, with ice scattering, and with an MCS, respectively. Results using TMI data matched within PR swath only are noted as TMI* in this study.

**Comparison of Long-Term Averages**

Fig. 17 compares rain estimates from the TMI, PR and GPCC gauge analyses over land on a $2.5^\circ \times 2.5^\circ$ grid. A linear regression analysis has been performed on the data, with the means of the two datasets being compared, correlation coefficient ($r$), and slope ($m$) of the fit presented in the legend. Each panel compares two of the datasets. In (a), the TMI and PR are compared. The TMI estimates are found to be 23% higher than the PR’s tropics-wide over land, which is roughly consistent with the 20% figure quoted by Kummerow et al. (2001) given the different land-ocean mask and different time periods used. Note that the slope values do not necessarily agree with the percent difference value because the y-intercept is not set to zero in the regression analysis. The correlation is high (0.93). It appears that the PR estimates more rainfall at lower rain rates, with the exception of a few outliers where the TMI is several factors greater than the PR. At higher rain rates, the TMI generally estimates more rainfall. Comparing the PR with the GPCC gauges in Fig. 17b, the GPCC gauges are about 8% higher than the PR. The correlation coefficient is about 0.88. However, there are a few points where the PR is several factors higher than the GPCC gauges despite having lower total mean rainfall. The TMI estimates are 33% higher than the GPCC estimates (Fig. 17c). Here the scatter of the points is much higher for heavier rain rates than comparing the GPCC and PR estimates, with many locations having TMI higher than GPCC. This fact lowers the correlation coefficient to 0.86.
Figure 17. Scatter plots of 2.5° × 2.5° TMI, PR, and GPCC over-land rainfall. (a) TMI versus PR, (b) PR versus GPCC, and (c) TMI versus GPCC on a log-log axis. The solid line is the 1:1 line, the dashed lines indicate 100% difference.
Gauge networks are sparse, especially in the deep tropics (see Fig. 16). The GPCC gauge analysis is interpolated to points that contain no gauges (Rudolf et al. 1994). Fig. 18 shows points where more than two gauges exist per 2.5° grid, which occurs in 133 boxes. This condition does not meet the 10% random error condition mentioned above for monthly rain estimates. However, combining 4 years of data mitigates this disadvantage. In both the PR (Fig. 18a) and TMI (Fig. 18b) comparisons with the GPCC gauge analysis, the same trends exist, with the GPCC gauge analysis now 2% (18%) lower than the PR (TMI). For the TMI versus GPCC analysis comparison (Fig. 18b), the scatter is especially reduced. However, there are few gauges in the GPCC gauge analysis in the heaviest raining areas as reported by the PR and TMI (locations with more than two gauges never exceed about 9 mm dy⁻¹).

Regional and Seasonal PR, TMI, and GPCC Gauge Comparisons

To show the geographic distribution of the estimates and their differences, Figs. 19 through 23 show in their respective panels: (a) GPCC gauge rainfall, (b) PR rainfall, (c) TMI rainfall, and absolute difference in rainfall between (d) TMI and PR, (e) PR and GPCC, and (f) TMI and GPCC. The resolution of the plots is 2.5° × 2.5°. The values correspond to the color bar at right, except in (a) though (c) rainfall values greater than 0.5 and less than 1.0 mm dy⁻¹ have been rounded to 1.0 mm dy⁻¹. Fig. 19 shows the rainfall estimates for the period December 1997 through November 2001, while Figs. 20 through 23 show them for the same period limited to the December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON) seasons, respectively.
Figure 18. Scatter plots of $2.5^\circ \times 2.5^\circ$ over-land rainfall in GPCC grid boxes with at least 2 gauges. (a) PR versus GPCC, and (b) TMI versus GPCC on a log-log axis. The solid line is the 1:1 line, the dashed lines indicate 100% difference.
Figure 19. Mean daily 2.5° × 2.5° rain estimates and differences for all seasons for the period December 1997 to November 2001. The panels show PR (a), TMI (b), and GPCC (c) rainfall (mm mon⁻¹), and differences (mm mon⁻¹) between the PR and TMI (d), PR and GPCC (e), and TMI and GPCC (f). Gray areas indicate no data.
Figure 20. Mean daily 2.5° x 2.5° rain estimates and differences for the DJF season for the period December 1997 to February 2001. The panels show PR (a), TMI (b), and GPCC (c) rainfall (mm mon⁻¹), and differences (mm mon⁻¹) between the PR and TMI (d), PR and GPCC (e), and TMI and GPCC (f). Gray areas indicate no data.
Figure 21. Mean daily $2.5^\circ \times 2.5^\circ$ rain estimates and differences for the MAM season for the period March 1999 to May 2001. The panels show PR (a), TMI (b), and GPCC (c) rainfall (mm mon$^{-1}$), and differences (mm mon$^{-1}$) between the PR and TMI (d), PR and GPCC (e), and TMI and GPCC (f). Gray areas indicate no data.
Figure 22. Mean daily $2.5^\circ \times 2.5^\circ$ rain estimates and differences for the JJA season for the period June 1999 to August 2001. The panels show PR (a), TMI (b), and GPCC (c) rainfall (mm mon$^{-1}$), and differences (mm mon$^{-1}$) between the PR and TMI (d), PR and GPCC (e), and TMI and GPCC (f). Gray areas indicate no data.
Figure 23. Mean daily 2.5° × 2.5° rain estimates and differences for the SON season for the period September 1999 to November 2001. The panels show PR (a), TMI (b), and GPCC (c) rainfall (mm mon⁻¹), and differences (mm mon⁻¹) between the PR and TMI (d), PR and GPCC (e), and TMI and GPCC (f). Gray areas indicate no data.
The main point of Figs. 19 through 23 is that the differences in the rain estimates differ on a regional and seasonal basis, especially over land regions where seasonality effects are more pronounced. Fig. 19 shows that the over-land estimates agree in a qualitative sense with the gauges (a) and PR (b) underestimating with respect to the TMI (c), especially in the deep tropics. These disparities show up in the difference maps (Fig. 19 d-f), where the TMI is more than twice the PR estimates over land areas like the Martitime Continent, equatorial Africa, tropical Australia, and coastline areas in Chile, Baja California, western Africa, and the Middle East. The latter coastline problems are due to a screening problem in the TMI algorithm where rain is assigned to selected artifacts caused by the coastline discontinuity (C. Kummerow, personal communication). Over the ocean, large TMI positive differences show up over the Pacific ITCZ, while the percentage differences are higher in the Central and East Pacific than the West Pacific because of lower rain rates in the East (Berg and Kummerow 2002). Lesser positive TMI-PR differences (of \( \leq 40\% \)) exist over large areas of the Amazon basin, and the Atlantic and Indian ITCZ. Contrarily, the PR exceeds the TMI in several higher latitude land regions, including inland areas in China, Mexico and the US, and South America, Africa, and Australia south of 30°S. The TMI is also greater than the PR in dry regions like North Africa, the Middle East, and the ocean areas dominated by the Subtropical highs.

Comparisons of the PR and TMI rainfall with the GPCC gauge rainfall appear in Figs. 19 (e) and (f), respectively. In examination of these figures, it is useful to keep in mind the gauge coverage map in Fig. 16, realizing that many land areas exist in the deep tropics without ample gauge coverage in the GPCC analysis, most obviously in
interior Africa. The gauge analysis is highly interpolated in these regions; large uncertainties in the calculated biases exist there as a result. PR overestimates exist with respect to the GPCC analysis over the Sierra Madre (however, gauges are likely at lower elevations than the rainfall maximum), extending into the central US (where gauge coverage is ample). Other areas with PR greater than GPCC occur in subtropical South America, mountainous areas like the Andes and Himalayas (where gauge coverage is poor along the slopes), Western Equatorial Africa, and the southern two-thirds of Australia. Over the Indian Subcontinent, Eastern Asia the PR is underestimating with respect to both the TMI and the gauges (an area with ample gauge coverage). In addition, the PR is underestimating (by roughly 20-40%) with respect to the gauges over the western African coast near the equator, the Amazon, the western African coast near the equator (both uniform rainfall areas), and the Maritime Continent region (an area dominated by local effects), especially near the coastlines.

The TMI overestimates in most significantly rainy regions of the over-land tropics with respect to the GPCC gauge analysis (Fig. 19f), with the notable exceptions of most of the over-land dry regions (apart from coastline and surface artifacts, e.g., the TMI’s unreasonable estimates in the Atacama Desert in Chile), south and east Asia, the southern two-thirds of Australia, and a few regions in the Southeast US and Mexico.

Seasonal rainfall amounts and differences appear in Figs. 20 though 23, presented as in Fig. 19. During DJF (austral summer), note the predominance of Southern Hemisphere rainfall (Fig. 20 a-c); the TMI estimates are generally higher than the PR’s by 20-40% over these areas (Fig. 20d), with the exceptions of interior Australia and South Africa where PR > TMI. Over the Northern Hemisphere during
this time period (boreal winter), the PR is higher than the TMI in many regions, with
the exception of Western North America (where high fractional differences exist, not
shown), the Pacific storm track, and light rain and coastline areas in Africa and Asia.
Note that many wintertime areas see small rain rates. The PR underestimates rainfall
most notably in the Amazon and Maritime Continent with respect to the GPCC gauges
(Fig. 20b) in DJF, except over the US, the Amazon and Subtropical South America,
southern Australia, and Africa (where gauge networks are sparse. The TMI
overestimates (underestimates) rainfall with respect to the GPCC gauges (Fig. 20c) in
most of the rainy Southern (Northern) Hemisphere. Again, dry, mountainous, and
coastline areas show, TMI>PR in both hemispheres.

Rainfall patterns in MAM shift northward (Fig. 21a-c); difference patterns
between the PR and TMI in MAM (Fig. 21c), for the most part, remain similar to those
in DJF (Fig. 20c), accounting for the change in rainfall locations. Note the high TMI
(PR) overestimates in Africa between 5° and 10°N (southeastern China), a dry (wet)
region in this season. PR and TMI differences with respect to the GPCC analysis
change significantly as well (Figs. 21 d and e). Both the PR and TMI differences
change sign in many areas in the Northern Hemisphere, especially over the US and
Asia. A corresponding sign shift occurs in Australia, but not to such a great extent.
Patterns in the oceanic ITCZs remain relatively consistent with the previous three
months; the TMI overestimate with respect to the PR in the Pacific storm track becomes
higher in magnitude, but fractionally consistent due to increasing rainfall there.

JJA features the furthest northward push of the over-ocean ITCZ and the boreal
summer over-land rainfall maximum in many Northern Hemisphere areas (Figs. 22a-c).
TMI overestimates with respect to the PR are widespread in the Northern Hemisphere and ITCZ (Fig. 22d), except over the eastern side Sierra Madre and Tibetan Plateau, and some areas of the Indian Subcontinent (coincident with the landfalling monsoon). Subtropical South America and Australia see PR estimates higher than the TMI’s. Estimates in these areas, as well as in North America, are also higher than the GPCC gauges (Fig. 22d). The PR, and to some extent the TMI (Fig. 22e), both underestimate in Asia with respect to the gauges, except along the coast where large negative gauge biases exist with respect to the TMI and PR in some regions. Similar to the PR-Gauge discrepancies, the TMI also overestimates over North America; however, the PR (TMI) overestimates with respect to the gauges more than the TMI (PR) in Southern Brazil (Venezuela). The Sahel (between 15° and 17.5°N north in Africa) is a region dominated by rainfall from MCSs during JJA (Mathon et al. 2002); here the PR overestimates with respect to both the gauges and the TMI as opposed to the regions further south.

The transition to the warm season in the Southern Hemisphere in SON brings rainfall back to Subtropical South America, the southern Congo Basin, and a decrease in rainfall in the Sierra Madre (Figs. 23 a-c); also a southward shift in the ITCZ. The transition season brings increased TMI overestimates with respect to the PR back to the southern hemisphere, especially over the Amazon; SON brings the highest absolute and fractional differences there. The TMI is also higher than the PR over Central and West Africa. PR positive biases with respect to the GPCC gauges decrease in North America, especially in the west (Fig. 23e), while PR positive biases return to Australia, Argentina, southern Brazil, and South Africa. TMI-gauge biases see more dramatic pattern shifts than the PR in this transition (Fig. 23f). Positive TMI biases are replaced
with negative ones in North America, while the trend is reversed over the Amazon and Australia. Positive biases are increased in many areas in Africa. Biases in the Maritime Continent and ocean areas remain nearly constant for both the PR and TMI with respect to the GPCC gauges.

The seasonal analyses show that the PR-TMI and TRMM-gauge biases remain more constant (with TMI > PR most often) in the low latitude land areas near the ITCZ where the rainfall regime is less seasonally dependent. However, significant biases do exist in low latitudes. The overestimate of the TMI with respect to the gauges over equatorial Africa is consistent with the findings of McCollum et al. (2000), who found that microwave ice scattering rainfall overestimation is related to climatologically dry air and more aerosols and thus lower rainfall efficiency for a given amount of ice scattering (as compared to a more moist regime like the Amazon or the South Asian Monsoon). Note, however, that the PR algorithm does not adjust its DSD parameters for low level moisture conditions in a given region, which introduces uncertainty in the PR retrieval. This also agrees with the TMI-PR comparisons of Masunaga et al. (2002) who find that TMI vertically-integrated precipitation water contents and rainfall are higher on a zonal basis than PR liquid water contents in the deep tropics. Subtropical warm seasons generally show positive TMI and PR versus gauge biases, the sign of the TMI-PR bias was regionally varying depending on the rainfall regime. During the subtropical cold seasons, the TMI, and especially the PR, are less than the GPCC gauge estimates over land. Masunaga et al. (2002) show that TMI subtropical cold season precipitation water contents are less than those of the PR when integrated zonally. However, rainfall estimates were similar, due to the inconsistent conversion of water
content to rainfall rate between the two algorithms. However, the results of the seasonal analysis in this study suggest that making conclusions on a zonal basis may be misleading; regional cold and transition season, maritime versus continental, and rainfall by feature type variations in the rainfall regime are strong influences in the TMI-PR biases and TMI and PR biases with respect to the gauges.

Seasonal Comparisons over the US

To minimize possible sources of random error from insufficient gauge coverage in gauge-lacking regions, the dense CPC gauge network is compared with the GPCC gauge, TMI, and PR estimates over the Southern US. The data presented here are on a $1^\circ \times 1^\circ$ grid, far beyond the resolution of any of the TRMM standard products, and sampling problems would be expected to be present. However, high resolution maps can be useful in elucidating these unresolved sampling problems and artifacts in the estimates. Fig. 24 shows the estimates for the entire 4-year period December 1997 through November 2001. The GPCC (Fig. 24a) and CPC (b) gauge analyses appear fairly consistent over most of the US considering that the CPC analysis contains more than an order of magnitude more stations. The TMI (c) and PR (d) estimates, in a very rough pattern, get the general patterns of the gauge rainfall correct. The PR and TMI show the east-west gradient of rainfall in the Southern Plains, and the maximum in the central Gulf Coast states. However, several disagreements exist between the algorithms. The PR estimates are higher than the TMI in the Gulf Coast states away from the coastline, while the TMI is higher along the coast. Overall, both the PR and TMI are higher (in agreement with the findings of McCollum et al. 2002), even in the Desert Southwest. The TMI also has what appears to be artifacts in the Sierra
Figure 24. Rain estimates over southern North America for all seasons for the period December 1999 to November 2001. GPCC (a), CPC (b), 2A12 TMI (c), and 2A25 PR (d) 1° × 1° mean daily rain estimates (mm mon⁻¹) are shaded. White areas indicate no data.
Mountains and Southern Utah/Northern Arizona deserts, possibly caused by surface screening effects due to snow cover and large lakes in the region. The rainfall estimates for the seasons DJF (Fig. 25), MAM (Fig. 26), JJA (Fig. 27) and SON (Fig. 28) elucidate the sampling and surface screening artifacts in the data TMI and PR estimates.

In the cold season (DJF) where snow cover is present in the West, gauge estimates are far from portraying reality (Fig 25a and b); however artifacts seem to show up in high TMI estimates in the Rocky Mountains and deserts (Fig. 25c).

In addition, some coastline effects seem apparent along the Gulf Coast, and there seems to be a trough in TMI rainfall corresponding with the Mississippi Valley compared with the gauges. The PR estimates seem free from large effects from artifacts (Fig. 25d), however factor-of-two overestimates in the Gulf Coast states are apparent. In MAM, TMI artifacts are still present in the West (Fig. 26c), and overestimates appear in the Southern Plains, although less in magnitude than those from the PR (Fig. 26d). Note the northward movement of the region of overestimation by the TMI and PR from DJF. During JJA, cold surface artifacts are not present in the TMI estimates (Fig. 27c). However, the coastline effect is present in many areas in the Southeast and Florida, although this appears to a lesser extent in the PR data during this season (Fig. 27d), indicative of possible sea breeze precipitation. However, the TMI still exceeds the PR by more than 25% in these regions. The inland overestimates by the PR are not present, although they appear poleward of 37° in the TMI rain estimates. This is outside the swath coverage of the PR. During SON, a likely surface artifact appears in southern Utah in the TMI estimates (Fig. 28c), along with overestimates with
Figure 25. Rain estimates over southern North America for the DJF season for the period December 1997 to February 2001. GPCC (a), CPC (b), 2A12 TMI (c), and 2A25 PR (d) 1° × 1° mean daily rain estimates (mm mon⁻¹) are shaded. White areas indicate no data.
Figure 26. Rain estimates over southern North America for the MAM season for the period March 1998 to May 2001. GPCC (a), CPC (b), 2A12 TMI (c), and 2A25 PR (d) 1° × 1° mean daily rain estimates (mm mon⁻¹) are shaded. White areas indicate no data.
Figure 27. Rain estimates over southern North America for the JJA season for the period June 1998 to August 2001. GPCC (a), CPC (b), 2A12 TMI (c), and 2A25 PR (d) 1° × 1° mean daily rain estimates (mm mon⁻¹) are shaded. White areas indicate no data.
Figure 28. Rain estimates over southern North America for the SON season for the period September 1998 to November 2001. GPCC (a), CPC (b), 2A12 TMI (c), and 2A25 PR (d) 1° x 1° mean daily rain estimates (mm mon⁻¹) are shaded. White areas indicate no data.
respect to the others along the Gulf Coast. Overall, however, the TMI and PR (c and d) estimates agree best with the gauge estimates (a and b) during SON.

Low emissivity land surfaces (i.e., snow cover, surface water, lakes) appear radiometrically similar to rain signatures at 85 GHz. Effects of surface scattering artifacts (i.e., snow cover, inland lakes) and coastlines present complications in scattering rainfall algorithms (Grody et al. 1991, Ferraro et al. 1998, Kummerow et al. 2001). Surface properties are highly spatially and temporally inhomogeneous, making the creation of artifact screening procedures difficult. It appears that the version 5 screening algorithm still needs improvement in order to remove some artifacts.

The overestimation problem by the instruments inland is likely not an artifact of surface properties; it is either due to a true algorithm bias or a sampling problem. At first glance, one would rule out sampling as a problem in this region because at the poleward extent of the TRMM satellite at 35° latitude, TRMM’s sampling is nearly twice that at the equator. However, these two (or sometimes three) satellite overpasses in the same location occur sequentially within a few hours of each other, as opposed to a more gradual precession through the diurnal cycle at low latitudes. It is hypothesized that the presence of heavy rainfall from large, long lived convective systems at high latitudes combined with the nonuniform diurnal sampling of the TRMM satellite, especially within the narrow PR swath, leads to an oversample of rainfall in this region. Fig. 29 shows the fraction of PF rainfall from MCSs seasonally for the period December 1997-November 2000. For each season, high fractions of rainfall from MCSs are coincident with regions with PR and TMI overestimates with respect to the gauges. The sampling by the TRMM satellite at this latitude in this MCS rainfall
Figure 29. Percent of PR 2A25 1° × 1° rainfall from MCS. Panels are separated for each season: (a) DJF 1997-2000, (b) MAM 1998-2000, (c) JJA 1998-2000, and (d) SON 1998-2000.
regime is hypothesized to be at least partially responsible for PR and TMI overestimates in this region, further study is necessary to quantify the role of this possible mechanism.

Seasonal Time Series of Regional Rainfall Estimates

To further examine the role of algorithm biases and orbital sampling errors among the rainfall estimates, this section presents time series of the estimates over large regions ($\geq 5^\circ \times 5^\circ$), as well as the fraction of rainfall from MCSs and number of MCSs in the given region from the PF database. Fig. 30a shows the PR (2A25), TMI (2A12), TRMM combined (3B43), GPI, GPCC gauge, and CPC gauge estimates over the Southern Plains of the US (bounded by 105$^\circ$ and 90$^\circ$W, 23$^\circ$ and 35$^\circ$N over land). Here the gauge estimates and the 3B43 estimates all track each other closely. However, the remote sensing estimates diverge, especially in the spring and summer seasons. The PR overestimates with respect to the TMI each MAM, when the fraction of rainfall from MCSs hits a relative maximum (Fig. 30b). Note that DJF 1997 has limited TRMM sampling beginning on 7 December 1997, after TRMM operations began; this season has additional complications due to the strong El Niño event that was occurring at this time. However, when MCSs play a large role in the rainfall budget, the PR and TMI (and also the GPI, which should not suffer from temporal sampling problems) overestimate by a large degree in that season at this high latitude location. Likewise, a similar pattern appears in Southern Brazil (bounded by 50$^\circ$ and 55$^\circ$W, 25$^\circ$ and 30$^\circ$S) in Fig. 31, where PR and TMI overestimate with respect to the gauges when the fraction of rainfall from MCSs is increased. In this case, estimates from the PR are more than three times the gauge estimates in SON 1998, and nearly twice the gauges in SON 1999 and 2000, with corresponding more modest overestimates by the TMI. In SON 1998,
Figure 30. Seasonal time series of rain estimates and MCS statistics over the Southern Plains of the US for the period December 1997 through November 2000. In each panel: (a) rainfall from the 2A25 (PR), 2A12 (TMI), 3B43, GPI, GPCC, and CPC estimates, and (b) fraction of rainfall from MCSs and number of MCSs from the precipitation feature database.
Figure 31. Seasonal time series of rain estimates and MCS statistics over Southern Brazil for the period December 1997 through November 2000. In each panel: (a) rainfall from the 2A25 (PR), 2A12 (TMI), 3B43, GPI, and GPCC estimates, and (b) fraction of rainfall from MCSs and number of MCSs from the precipitation feature database.
the PR produces 420 mm mon\(^{-1}\) from 11 MCSs that are responsible for about 90% of the rainfall. Such extremely MCS-dominated rain estimates strongly suggest that the TMI and especially the PR estimates are suffering from orbital sampling problems at these locations in high latitudes. To contrast areas at higher latitudes, two low latitude areas are compared here: the Sudan (Fig. 32, covering 20° to 30°E, 5° to 15°N) and the eastern Amazon (Fig. 33, covering 50° to 60°W, 10°S to the equator). Over the Sudan (Fig. 32), there is a strong seasonal modulation in the fraction of rainfall from MCSs, reaching 60-70 percent in SON. We see only slight PR overestimates in these seasons, compared with excellent PR-gauge agreement in the less MCS-dominated seasons. The TMI consistently overestimates in this region, in agreement with the findings presented above and those of McCollum et al. (2000). In the eastern Amazon (Fig. 33), the fraction of rainfall from MCSs is lower than the aforementioned regions, so the impacts of them are minimized on the rainfall budget as well as on orbital sampling considerations. As expected, PR estimates are not biased high accordingly (they are actually lower than the gauge estimates and significantly lower than the overestimates by the TMI with respect to the GPCC gauge analysis).

This section has outlined that despite tropics-wide agreement within 25% of the TRMM and gauge estimates, there are significant regional and seasonal biases in the estimates due to differences in the algorithms, surface artifacts, and errors introduced by orbital sampling of MCS-dominated rainfall regimes at high latitudes. The remaining sections will eliminate the effects of sampling due to differing swath widths and look at comparisons of the PR and TMI algorithms on a feature by feature basis,
Figure 32. Seasonal time series of rain estimates and MCS statistics over the Sudan for the period December 1997 through November 2000. In each panel: (a) rainfall from the 2A25 (PR), 2A12 (TMI), 3B43, GPI, and GPCC estimates, and (b) fraction of rainfall from MCSs and number of MCSs from the precipitation feature database.
Figure 33. Seasonal time series of rain estimates and MCS statistics over the eastern Amazon for the period December 1997 through November 2000. In each panel: (a) rainfall from the 2A25 (PR), 2A12 (TMI), 3B43, GPI, and GPCC estimates, and (b) fraction of rainfall from MCSs and number of MCSs from the precipitation feature database.
only within the PR swath, to examine differences in the algorithms by rainfall system type.

**Feature-by-Feature Comparisons of the PR and TMI Algorithms**

The remainder of this study focuses on comparing the PR and TMI estimates normalizing for sampling differences of the instruments by comparing the estimates within the PR swath only (TMI estimates within the PR swath are denoted as TMI*) for the period March through August 2002. In addition, the PF definition has been modified to include all areas that are assigned as raining according to the PR or TMI to allow the investigation of rainfall biases by precipitation feature type.

Table 1 shows the total and conditional rain rates for each precipitation feature type for both the PR and TMI* estimates over land or ocean. Total rain rate is defined as the total rain volume divided by the total number of pixels sampled, conditional rain rate is the total rain volume divided by number of pixels with nonzero rain rates from either the PR or TMI in the PFs (i.e., the “rain rate where the PR or TMI estimates that it is raining”). Note that this definition will serve to lower the PR conditional rain rate relative to the TMI because of the larger areal coverage of the TMI rain area into non-raining PR pixels due to beam filling (mainly over ocean) and the spreading of ice scattering signatures beyond the rain area (mainly over land). In addition, TMI conditional rain rates will be lower due to larger pixel sizes (by a factor of 1.9). Despite this, for all features over land, the TMI* is 24.7% higher than the PR for this period (26.1% higher than over ocean). Over land the conditional rain rate of the TMI* is 40.5% higher than the PR, whereas over the ocean it is 13.3% lower. Note also that the PR’s total and conditional rain rates are much more similar over land and ocean; the
Table 1: Total and conditional PR and TMI* rain rates and their percentage differences for all precipitation features and by feature type.

<table>
<thead>
<tr>
<th></th>
<th>Total (mm/day)</th>
<th>Conditional (mm/hr)</th>
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<tbody>
<tr>
<td></td>
<td>PR TMI* % (TMI-PR) PR TMI* % (TMI-PR)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land</td>
<td>2.51 3.13 24.7%</td>
<td>3.14 4.41 40.5%</td>
</tr>
<tr>
<td>Ocean</td>
<td>2.36 2.98 26.1%</td>
<td>2.38 2.06 -13.3%</td>
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<tr>
<td>MCS</td>
<td></td>
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<tr>
<td>Land</td>
<td>1.34 2.00 49.0%</td>
<td>4.42 5.97 34.9%</td>
</tr>
<tr>
<td>Ocean</td>
<td>1.23 1.87 52.6%</td>
<td>3.47 3.68 6.0%</td>
</tr>
<tr>
<td>WI</td>
<td></td>
<td></td>
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<tr>
<td>Land</td>
<td>0.86 0.95 10.3%</td>
<td>3.60 3.92 9.1%</td>
</tr>
<tr>
<td>Ocean</td>
<td>0.66 0.87 30.6%</td>
<td>2.55 1.98 -22.4%</td>
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<tr>
<td>NI</td>
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<td>Land</td>
<td>0.30 0.18 -41.5%</td>
<td>1.58 1.31 -17.0%</td>
</tr>
<tr>
<td>Ocean</td>
<td>0.47 0.27 -43.0%</td>
<td>1.56 0.73 -53.6%</td>
</tr>
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</table>
TMI*'s conditional rain rate is more than a factor of two higher over land than ocean. This is partially due to a higher minimum detectable rainrate threshold in the TMI algorithm over land than ocean because surface screening must be more conservative (C. Kummerow, personal communication), however histograms of conditional rain rate presented later will also indicate an algorithmic positive bias.

The paradox over ocean of higher TMI* total rain rates and lower TMI* conditional rain rates than the PR can be investigated by breaking the total rainfall into the three PF types. For MCSs, the TMI* rain rate from MCSs is 49% and 53% higher than the PR MCS rain rate over land and ocean, respectively. TMI* MCS conditional rain rates are also higher than the PR’s, although much more so over land than ocean; they agree within 6% over ocean. For PFs WI, the total rain rates from the TMI* and PR differ by 10% over land and 31% over ocean, more comparable than MCS rain rates. Conditional rain rates over land are only 9% high from the TMI*, although they are 22.4% higher from the PR for features WI over ocean. For NI features, the PR gives higher total and conditional rain rates for both land and ocean categories by 17% and 54% over land and ocean, respectively, although it is likely that beam filling and mismatching is a difficulty here. The resulting trend is that the TMI* overestimates compared to the PR for MCSs by roughly 50% over both land and ocean, and by a lesser degree (10% and 31% over land and ocean, respectively) for features WI, whereas the PR overestimates relative to the TMI* for NI features by roughly 40% over land and ocean.

Scatter plots of PR and TMI* estimates by PF type over land and ocean areas appear in Fig. 34. The estimates have been placed in a $1^\circ \times 1^\circ$ grid. For MCSs (a) and
Figure 34. Scatter plots of TMI* versus PR $1^\circ \times 1^\circ$ rainfall (mm mon$^{-1}$) by precipitation features. Each panel shows: (a) MCSs over land, (b) PFs WI over land, (c) PFs NI over land, (d) MCSs over ocean, (e) PFs WI over ocean, and (f) PFs NI over ocean on a log-log axis. Solid line indicates the one to one line, while the dashed lines indicate a 100% difference.
PFs WI (b) over land, the positive mean biases for the TMI* are evident, although there are a few outliers in the MCS panel (a) with high rain rates with almost no PR rainfall. This pattern also shows up in the over land NI feature panel in (c); however the vast majority of points show the PR with higher estimates than the TMI*. Following Table 1, the over-ocean values follow the same general pattern (d-f). There are some differences, however. The MCS (d) and NI (f) over ocean panels do not show the outlier points with high TMI* rain rates and low PR rain rates; this suggests that the over-land outliers are locations dominated by artifacts. Also, for the WI panel (e) shows that the TMI* increases its fractional overestimates at high rain rates (as indicated by the number of points above the best-fit line).

The geographic distribution of PR and TMI* rain rates (and their percent difference normalized to the PR rainfall) in total and by feature type appears in Figs. 35-38 at 0.5° × 0.5° resolution (smoothed with a 1:2:1 spatial weighting filter). Because of the pixel-by-pixel match between PR and TMI* estimates, the lack of random error introduction from sampling differences allows a high resolution investigation of the biases in order to highlight small scale bias features that would be hidden by areal averaging. For total PR and TMI* rain rates from all feature types (Fig. 35), most heavily raining areas in the ITCZ show that the PR (a) is underestimating with respect to the TMI* (b). This is borne out in the percent difference panel (c), with most areas in the low latitudes having TMI* > PR by 0 to 50%, while western and central Africa south of 12°N, the central and east Pacific, and South Pacific Convergence Zone have many areas with TMI* greater than the PR by more than 50%. Some notable exceptions in low latitude areas with PR > TMI* include the Sahel
Figure 35. Maps of differences between the PR and TMI* total estimates. The panels show (a) PR and (b) TMI* rainfall and (c) their fractional differences in mm day$^{-1}$ for the period March through August 2002.
Figure 36. Maps of values of, and differences between the PR and TMI* MCS estimates. The panels show (a) PR and (b) TMI* MCS rainfall and (c) their fractional differences in mm hr⁻¹ for the period March through August 2002.
Figure 37. Maps of the values of, and differences between the PR and TMI* WI estimates. The panels show (a) PR and (b) TMI* WI rainfall and (c) their fractional differences in mm hr$^{-1}$ for the period March through August 2002.
Figure 38. Maps of the values of, and differences between the PR and TMI* NI estimates. The panels show (a) PR and (b) TMI* NI rainfall and (c) their fractional differences in mm hr$^{-1}$ for the period March through August 2002.
around 17°N, coastal Brazil, eastern Africa, and many near-desert areas. Midlatitude areas see more of a mixed pattern: areas in the southern US along the coastlines (especially Baja California) and areas in northern Argentina have TMI* estimates greater than the PR’s, however southern Australia, inland eastern China, the Tibetan Plateau, the Middle East, and the Sierra Madre have PR > TMI*.

Fig. 36 shows the geographic pattern of the MCS PR (a) and TMI* (b) rain rate estimates and corresponding fractional biases (c). Almost everywhere in the low latitudes, the TMI* is overestimating by more than 50% (with over 100% differences over the East and Central Pacific, Amazon, and equatorial Africa), with lesser TMI* overestimates between 0 and 50% in the midlatitudes. There exists some notable areas of MCS PR > TMI* (although much smaller in magnitude–less than 50%–compared with the TMI* > PR regions in the low latitudes), including eastern China, inland North America, southern Brazil, Argentina, Uruguay, Australia, and east of the Cape of Good Hope, all regions where it is raining significantly. Also, dry areas like South Australia, and the dry and mountainous regions of Africa and Asia contain regions of MCS PR>TMI*.

For features WI (Fig. 37), the TMI* (a) is significantly higher than the PR (b) over the southern Amazon and central Africa. Overestimates by the TMI* between 0 and 50% occupy most of the low latitudes globally (c); overestimates are lower in magnitude for features WI than for MCSs (see Fig. 36). However, there are still many locations with factor of two overestimates. Midlatitude areas tend to see PR > TMI*, including Subtropical South America (especially in Argentina and Southern Brazil), the Sierra Madre, the inland southeast US, and China. In the North Pacific storm track, the
TMI* is significantly higher than the PR. NI features rainfall amounts are significantly higher from the PR (Fig. 38a) than from the TMI* (b). We believe that this is largely because of beam filling and sensitivity issues with the TMI. This results in 50% to 100% higher estimates from the PR (c) in most areas. However, several areas over land have TMI* higher than the PR by over 100%, mainly in dry areas. This may be due to radiometrically cold surface or coastline artifacts in several areas including the Atacama, Namibian, and Southwest US deserts.

Other Characteristics of the Retrievals Leading to Differences

Other characteristics of the retrieved rainfall from the PR and TMI* can yield information about algorithm performance. Convective and stratiform rainfall modes contain distinctly different rain rate histograms and DSDs; the ability for a remote sensing algorithm to identify such areas can improve the prospects for accurate rain estimation. The PR has the ability to do so with considerable skill due to its ability to retrieve the rain profile and better vertical resolution, which allows the detection of brightband signatures, and horizontal inhomogeneities often observed with stratiform and convective rain, respectively. Spaceborne radar techniques, however, can have difficulties due to beam filling effects. Techniques have been used at 85 GHz to separate convective and stratiform rains using the horizontal homogeneity of the high resolution ice scattering signature (Hong et al. 1999) and increased 85 GHz polarization differences in stratiform versus convective footprints (Olson et al. 1999). However, their skill is less than radar-based algorithms, especially for systems with weak ice scattering signatures due to a lack of sensitivity and beam filling problems. However, a convective-stratiform separation has been applied to the TMI* version 5 products
(Kummerow et al. 2001), but not over land in this version. A prototype ice scattering convective-stratiform algorithm has been developed for the future version 6 algorithm (McCollum and Ferraro 2002), but is not employed in this study.

To evaluate the portioning of rainfall among convective and stratiform pixels according to the PR convective-stratiform separation, Table 2 presents the mean fraction of rain and conditional rain rate assigned to convective, stratiform, and “other” (not classified as either convective or stratiform) for all PF types. Here, the convective and stratiform “certain,” “probably,” and “maybe” rain-type flags are used from the PR algorithm, assigning even the lowest confidence convective- and stratiform-identified pixels to each category. The table shows that over land, convective rainfall is 60.1% of the total, stratiform rainfall about 39.4%, and other rain types are about 0.5%. Over the same areas, the TMI* assigns 26.8% of its total rain to convective areas, 51.5% to stratiform areas, and 21.7% of its rain to other pixels classified by the PR. The assignment of TMI* rainfall to “other” areas occurs outside the PR raining area due to the spreading of the anvil’s ice scattering signature beyond the actual area of rain at the surface, and also over surface artifacts. Differences in the conditional rain rates over these regions are also apparent. The PR’s convective conditional rain rate over land is 9.75 mm hr\(^{-1}\), while the TMI* value is quite similar despite the effects mentioned above: 8.66 mm hr\(^{-1}\). However, the stratiform TMI* over land conditional rain rate (4.87 mm hr\(^{-1}\)) is a factor of 3.2 higher than the PR value of 1.51 mm hr\(^{-1}\). Also, the TMI* conditional rain rate in “other” pixels is 2.44 mm hr\(^{-1}\), significantly higher than the value of 0.46 mm hr\(^{-1}\) from the PR, which is close to the PR’s minimum detectable rain rate. Over the ocean, the problem is also present (15% of TMI* rainfall is in PR-
Table 2. Percent of total rain and mean conditional rain rates from the PR and TMI for all PF types as a function of location over land or ocean and rain type as determined by the PR.

<table>
<thead>
<tr>
<th></th>
<th>PR</th>
<th>TMI*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent of Total Rain</td>
<td>Conditional (mm/hr)</td>
</tr>
<tr>
<td>Land</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conv</td>
<td>60.12</td>
<td>9.75</td>
</tr>
<tr>
<td>Strat</td>
<td>39.42</td>
<td>1.51</td>
</tr>
<tr>
<td>Other</td>
<td>0.46</td>
<td>0.53</td>
</tr>
<tr>
<td>Ocean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conv</td>
<td>47.19</td>
<td>7.13</td>
</tr>
<tr>
<td>Strat</td>
<td>52.45</td>
<td>1.51</td>
</tr>
<tr>
<td>Other</td>
<td>0.36</td>
<td>0.50</td>
</tr>
</tbody>
</table>
defined convective areas, where the PR retrieves 47% of its rainfall) despite the presence of convective-stratiform information in the algorithm, however the TMI* over ocean stratiform conditional rain rate is only 1.9 times the PR’s, having a lower impact on the TMI positive bias.

Table 3 gives statistics for the features classified as MCSs. The same patterns exist for MCSs and as the total rainfall as described above. Even for MCSs, where convective-stratiform portioning should follow the classic model most often, TMI* over-land stratiform rain rates are a factor of 2.9 over PR rain rates, while they are a factor of 2.0 higher over ocean. For features WI (Table 4), the factor of 2.6 and 1.5 overestimates for the TMI stratiform rain rates over land and ocean, respectively, are balanced by higher convective conditional rain rates from the PR, especially over ocean where they exceed the PR by a factor of 2.2. For MCSs and PFs WI, there is a significant amount of TMI* rain outside the PR’s convective-stratiform classification: around 18% for MCSs, and 26.5% and 38.5% for land and ocean PFs WI. This showcases the larger footprints in the case of ocean retrievals, beam filling, and the extent of anvils beyond the PR raining area. For features NI (Table 5), beam filling and sensitivity become much more dominant factors in the TMI* retrieval, as convective TMI* rain rates are much lower than their PR counterparts. Stratiform retrievals for PFs NI see comparable rain rates between the two instruments; “other” pixels see the majority of rainfall from the TMI* while around 1% of the PR rainfall falls in these pixels, signaling difficulties in matching the PR and TMI* due to resolution, parallax, and scan geometry issues causing improper matches of the two instruments.
Table 3. Percent of total rain and mean conditional rain rates from the PR and TMI for MCSs as a function of location over land or ocean and rain type as determined by the PR.

<table>
<thead>
<tr>
<th></th>
<th>PR</th>
<th>TMI*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent of Total Rain</td>
<td>Conditional (mm/hr)</td>
</tr>
<tr>
<td>Land</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conv</td>
<td>61.53</td>
<td>12.48</td>
</tr>
<tr>
<td>Strat</td>
<td>38.20</td>
<td>2.09</td>
</tr>
<tr>
<td>Other</td>
<td>0.27</td>
<td>0.55</td>
</tr>
<tr>
<td>Ocean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conv</td>
<td>48.34</td>
<td>10.13</td>
</tr>
<tr>
<td>Strat</td>
<td>51.48</td>
<td>2.12</td>
</tr>
<tr>
<td>Other</td>
<td>0.17</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Table 4. Percent of total rain and mean conditional rain rates from the PR and TMI for PFs WI as a function of location over land or ocean and rain type as determined by the PR.

<table>
<thead>
<tr>
<th></th>
<th>PR</th>
<th>TMI*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent of Total Rain</td>
<td>Conditional (mm/hr)</td>
</tr>
<tr>
<td>Land</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conv</td>
<td>61.92</td>
<td>9.18</td>
</tr>
<tr>
<td>Strat</td>
<td>37.69</td>
<td>1.54</td>
</tr>
<tr>
<td>Other</td>
<td>0.39</td>
<td>0.54</td>
</tr>
<tr>
<td>Ocean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conv</td>
<td>47.69</td>
<td>6.78</td>
</tr>
<tr>
<td>Strat</td>
<td>52.01</td>
<td>1.50</td>
</tr>
<tr>
<td>Other</td>
<td>0.30</td>
<td>0.50</td>
</tr>
</tbody>
</table>
Table 5. Percent of total rain and mean conditional rain rates from the PR and TMI for PPs NI as a function of location over land or ocean and rain type as determined by the PR.

<table>
<thead>
<tr>
<th>Location</th>
<th>Type</th>
<th>PR</th>
<th>TMI*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent of Total Rain</td>
<td>Conditional (mm/hr)</td>
<td>Percent of Total Rain</td>
</tr>
<tr>
<td>Land</td>
<td>Conv</td>
<td>48.44</td>
<td>5.64</td>
</tr>
<tr>
<td></td>
<td>Strat</td>
<td>50.06</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>1.50</td>
<td>0.53</td>
</tr>
<tr>
<td>Ocean</td>
<td>Conv</td>
<td>43.36</td>
<td>4.81</td>
</tr>
<tr>
<td></td>
<td>Strat</td>
<td>55.71</td>
<td>1.07</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>0.93</td>
<td>0.50</td>
</tr>
</tbody>
</table>
The geographic distribution of the fraction of PR and TMI* 2.5° × 2.5° gridded rainfall convective, stratiform, and other according to the PR convective-stratiform classification appears in Figs. 39, 40, and 41 respectively. Note that the sum of the convective, stratiform, and other (not shown) components gives the total rainfall. The convective rain fraction from the PR is higher over land as would be expected due to the more intense convection there (Fig. 39a). This spatial pattern is seen in the TMI* (b), however, the magnitude is greatly reduced. Also, the highest TMI* convective rainfractions are reserved to selected subtropical land areas and equatorial Africa. The fractional difference plot (c) shows this, with reduced TMI* underestimates of convective rain fractions over the Southeast US, Subtropical South America, equatorial Africa, and northern India. This agreement is likely due to the strong ice scattering signatures in these regions which allows the TMI* algorithm to match heavy rain rates with the appropriate convective pixels.

The fraction of rain stratiform from the PR and TMI and their fractional differences appear in Fig. 40. The PR stratiform rain fraction (a) appears to a great extent lower than TMI* values (b) over most land areas, while over ocean they appear much more similar. Fractional differences (c) are within 20% over most ocean regions, while over land TMI* stratiform fractions are significantly higher than the PR*, especially in, but not limited to, the high convective fraction regions mentioned previously.

An illustration of the geographic location of the fraction of rainfall in pixels classified as “other” appears in Fig. 41. For the PR (a), this rain occurs in desert regions over land (the Sahara, Middle East, and Australia), and in areas with rainfall
Figure 39. Convective characteristics of the estimates. The panels show (a) PR, and (b) TMI*, and (c) their fractional difference of fraction of rainfall convective according to the PR convective-stratiform classification for the period March through August 2002.
Figure 40. Stratiform characteristics of the estimates. The panels show (a) PR, and (b) TMI*, and (c) their fractional difference of fraction of rainfall stratiform according to the PR convective-stratiform classification for the period March through August 2002.
Figure 41. Other characteristics of the estimates. (a) PR and (b) TMI* fraction of rainfall “other” according to the PR convective-stratiform classification for the period March through August 2002.
from stratocumulus clouds over the oceans. In the TMI*, the fraction of rain in the other pixels is greatly increased over most areas, maximized over the stratocumulus rain regions. It is lowest over land in the heavy rain regions (less than 20%) where the ice scattering matches well spatially with the precipitation. Over the oceans, beam filling is more of a problem due to the larger TMI emission footprints; this likely is the cause of the higher “other” fractions in heavily raining ocean regions with respect to over-land areas.

A comparison of the gridded 2.5° × 2.5° PR and TMI* conditional rain rates appears in Fig. 42. PR conditional rain rates (a) are maximized over land where the dominant mode of rainfall is convective (and the PR rain estimate may be more susceptible to errors in the attenuation correction). However, the TMI* (b) agrees that conditional rain rates are higher over land; however, they are biased higher than the PR and the presence of coastline artifacts tropics wide are present, also surface effects (in areas like the Sahel and Kashmir) are very apparent here. These areas have conditional rain rates between two and three times the surrounding land and ocean areas. Over areas not affected by artifacts over land, the TMI* conditional rain rates are often more than 20% higher than the PR’s (c). Over the ITCZ the conditional rain rates agree within 20% over most areas, while in non-ITCZ over-ocean areas the PR has higher conditional rain rates.

Conditional rain rate differences between the PR and TMI* are a function of PF type (see Tables 3-5). Fig. 43 shows the differences only for MCSs. The PR estimates the heaviest MCS conditional rain rates in the midlatitude MCS areas of the US and Subtropical South America, as well as limited areas of equatorial Africa. The TMI*
Figure 42. Total conditional rain rate characteristics of the estimates. (a) PR and (b) TMI*, and their differences of total conditional rain rate (mm hr$^{-1}$) for the period March through August 2002.
Figure 43. PF with MCS conditional rain rate characteristics of the estimates. (a) PR and (b) TMI*, and their differences of MCS conditional rain rate (mm hr$^{-1}$) for the period March through August 2002.
estimates more extensive areas with high conditional rain rates (b) including the Sahel, south of the Himalayas, and the Maritime Continent, these higher TMI values are borne out in the difference panel (c). For most of the ITCZ, the values are within 20%; however the PR is greater than the TMI* over ocean in the Southern Hemisphere south of 30°.

PFs’ WI conditional rain rates are shown in Fig. 44. For nonartifact-affected areas over land, the TMI* is relatively consistent with the PR*, with a tendency to slightly overestimate respective to the PR over areas like the Amazon, for example. However, artifacts along the coastlines are present in most areas, especially in the Maritime Continent, where TMI* conditional rain rates are more than double the PR’s. Over the ocean, PF WI conditional rain rates are biased low with respect to the PR.

For PFs NI (Fig. 45), PR NI conditional rain rates (a) are higher than the TMI* (b) over most of the domain; however some of the coastal artifacts still show up in the TMI* estimates in the coastal areas. The TMI* estimates of conditional rain rate over land are higher than over ocean; that land-ocean distinction is not present in the PR retrievals; the over-land values are more in agreement. A more quantitative comparison of conditional rain rates accounting for sensitivity and resolution issues will be left for future work.

Rain Rate Histograms

To further examine the differences in the algorithms, probability distribution functions (PDFs, black lines) and cumulative distribution functions (CDFs, gray lines) of the fraction of rain volume as a function of rain rate and PR convective-stratiform classification for the PR (solid lines) and TMI* (dashed lines) are analyzed for land and
Figure 44. PF WI conditional rain rate characteristics of the estimates. (a) PR and (b) TMI*, and their differences of PF WI conditional rain rate (mm hr⁻¹) for the period March through August 2002.
Figure 45. PF NI conditional rain rate characteristics of the estimates. (a) PR and (b) TMI*, and their differences of PF NI conditional rain rate (mm hr⁻¹) for the period March through August 2002.
ocean areas. Fig. 46 examines the distributions for MCSs. For MCS convective pixels over land (a), there is a smooth distribution of rain rates according to the PR, the TMI* distribution is jagged due to the use of only a selection of model database points matching the NESDIS operational algorithm. This results in certain rain rate bins being selected and others without representative database points not being selected. The maximum database point for the TMI* is 49.9 mm hr$^{-1}$, and 17% of the TMI MCS convective over-land rainfall occurs at this rain rate. At this point, by definition, all of the TMI* rainfall occurs at or below this rain rate as shown by the CDF. However, the PR still assigns about 20% of its total rain volume above this rain rate. This fact leads partially leads to the underestimate by the TMI* in these convective pixels.

In stratiform MCS pixels over land (b), the reverse is true. The TMI assigns over 40% pixels to the 10-15 mm hr$^{-1}$ range, while the PR assigns less than 5% of its rain volume in its pixels above 10 mm hr$^{-1}$. Note the presence of nonstratiform rain rates (e.g., the peak at 49 mm hr$^{-1}$ associated with an intense ice scattering pixel in a PR-defined stratiform region). In “other” pixels, almost all of the PR pixels have rain rates less than 1 mm hr$^{-1}$; the TMI* has significant rain volume contributions (>5%) in bins up to 15 mm hr$^{-1}$. Over ocean, the same patterns exist despite a more continuous rain rate distribution available for selection in the TMI* algorithm model database. Ocean convective MCS pixels have higher median rain rates in the PR (d), TMI* stratiform MCS rain rates are higher than those from the PR (e), although the agreement is much better between the two over ocean than land (see panel b). The “other” pixel MCS PR and TMI rain volume distributions are also more similar over ocean (e) than land (see panel c).
Figure 46. Characteristics of the rain rate histograms for MCSs. PR (solid lines) and TMI* (dashed lines) of the PDF (black lines) and CDF (grey lines) of rain volume as a function of rain rate over land (a-c) and ocean (d-f) for MCSs for the period March through August 2002.
For PFs WI (Fig. 47), convective over land TMI* pixels (a) see a significant fraction of the TMI* rain rates also occur at 49 mm hr\(^{-1}\), however, the total rain estimate again remains below that from the PR. For stratiform over land WI pixels (b), there is also a relative maximum in the contribution to total TMI* rain rates at rain rates 10-15 mm hr\(^{-1}\), and from “other” pixels (c) at rain rates greater than 1 mm hr\(^{-1}\), leading to the greater than factor of four overestimate by the TMI* relative to the PR for these pixels. Over the ocean (panels d-f), the convective rain rate TMI* PDF is more weighted to light rain rates than the PR, leading to the underestimate by the TMI*. The reverse is true for ocean WI stratiform rain rate distributions, leading to a 16% overestimate by the TMI*. Ocean “other” rain volume distributions (e) are weighted towards lighter rain rates than over-land distributions (see panel c); however, the overestimate by the TMI* is similar, more than a factor of four for “other” pixels.

For PFs NI (Fig. 48), the TMI* rain estimates are significantly less than the PR, the TMI* rain rates are heavily skewed lower than the PR’s over land in convective pixels (a). This is true to a lesser extent in over land stratiform pixels; however “other” pixels show an overestimate by a factor of 4.4. The same results are apparent over ocean in NI features, although the TMI* overestimate for “other” pixels is less (only a factor of 1.9). These differences again highlight the beam matching problems in small features; with many features having their rain rates assigned to nonraining pixels according to the other instrument.

These differences in the rain rate histograms, along with the TMI*’s assignment of “convective” rain rates to “stratiform pixels,” are major causes in differences between the TMI* and PR version 5 estimates. The TMI*’s higher
Figure 47. Characteristics of the rain rate histograms for PF WI. PR (solid lines) and TMI* (dashed lines) of the PDF (black lines) and CDF (grey lines) of rain rate as a function of rain rate over land (a-c) and ocean (d-f) for PFs WI for the period March through August 2002.
Figure 48. Characteristics of the rain rate histograms for PF NI. PR (solid lines) and TMI* (dashed lines) of the PDF (black lines) and CDF (grey lines) of rain volume as a function of rain rate over land (a-c) and ocean (d-f) for MCSs for the period March through August 2002.
stratiform conditional rain rate, combined with its higher stratiform and “other” pixel conditional rain rates leads to its overestimate of rainfall in MCSs and PFs WI. This is partially due to the misassignment of higher typically convective conditional rain rates to stratiform and “other” pixels in the TMI* compared to the PR and convective rain rates being slightly less from the TMI* than PR (partially because of pixel size differences), but it is also likely the result of an inappropriate ice scattering-rainfall relationship in stratiform regions.

Feature-by-Feature Comparisons

The precipitation feature database also allows rainfall estimate comparisons on a feature-by-feature basis, which can identify rainfall biases by system type; examination of the characteristics of these systems can lead to reasons why the estimates diverge. Fig. 49 shows a two-dimensional PDF of corresponding volumetric rain estimates from the TMI* and PR for each PF type over land and ocean, the color scale gives the relative frequency of occurrence of estimates in that box. Note the logarithmic scale; the bin sizes are 0.1 logarithmic volumetric rain units (mm hr⁻¹ km²). The solid line indicates estimates that are in agreement, the dashed lines on either side of the solid line indicate factor of 2 disagreements among the estimates. The mean volumetric rain bias for each PF type is indicated in each panel.

For MCSs over land (a), almost all of the features have TMI* estimates greater than the PR’s. However, there are a few features with PR > TMI*. Also, at PR MCS volumetric rain amounts less than $10^4$ mm hr⁻¹ km², there are some spurious features with disagreeing estimates (likely artifacts). For PFs WI over land (b), the TMI* is greater than the PR for the most part for high rain volume features (above $10^4$ mm hr⁻¹
Figure 49. Two-dimensional PDFs of TMI* versus PR feature-by-feature volumetric rainfall by PF type. Each panel shows (a) MCSs over land, (b) PFs WI over land, (c) PFs NI over land, (d) MCSs over ocean, (e) PFs WI over ocean, and (f) PFs NI over ocean.
Figure 49. (continued)

 NI Ocean

 Mean Bias = -3.3414%

 WI Ocean

 Mean Bias = 32.7377%

 MCS Ocean

 Mean Bias = 43.4090%
km$^2$), below this value the PR is equal to or greater than the TMI* for features with PR rainfall $> 10^3$ mm hr$^{-1}$ km$^2$. Below this value, the TMI* is several factors higher than the PR for these PFs, where beam filling problems become more important for smaller systems. For features NI over land (c), the estimates agreement is decreased with respect to the other feature types, and discrete values see higher relative occurrences due to the finite numbers of pixels in the smallest feature and the limited number of rain rates applied to the pixels in the TMI algorithm over land. The mean bias is for the PR to be greater than the TMI*; this is likely due to sensitivity and beam filling effects with these small, weakly ice scattering features.

MCSs over ocean (d) also have mean volumetric rainfall higher from the TMI* than from the PR with a very small minority of MCSs with PR volumetric rain greater than the TMI*; note the lack of spurious features at the low volumetric rain end of the spectrum. The occurrence of these spurious features at the low end of the rain volume spectrum is also lessened for PFs without ice scattering over the ocean (e). The same general pattern of bias is seen as over land for PFs without ice scattering, with higher rain volume features having TMI*>PR above $10^4$ mm hr$^{-1}$ km$^2$, PR is generally greater for features with lesser rain volumes. For features without ice scattering (f), the majority of features have PR > TMI*; with a much smoother distribution of rain rates available from the TMI* algorithm the distribution is much more uniform. However, there is a good deal of scatter due to sensitivity, beam filling, and beam matching difficulties.

To look at the distribution of the estimates’ absolute differences on a feature-by-feature basis, Fig. 50 shows cumulative distribution functions of the difference between
Figure 50. The distribution of differences in the estimates. CDFs of PR-TMI* for (a) MCSs over land, (b) PFs WI over land, (c) PFs NI over land, (d) MCSs over ocean, (e) PFs WI over ocean, and (f) PFs NI over ocean.
Figure 50. (continued)
the TMI* and PR volumetric rain estimates by feature type over land and ocean. The extent of the line in the horizontal direction gives the parameter space of the differences. For MCSs over land (a), we can see that the distribution is heavily weighted towards positive TMI* volumetric rain being greater than the PR; about 85% of the features have TMI* estimates greater than the PR’s. For features with (b) and without (c) ice scattering, we can see that the tails of the distributions are much more spread from the median value. This is because a much wider variety of storm types are classified as these storms, including, most notably, midlatitude fronts that are large but sometimes not convectively intense enough to be classified as MCSs. Most of these features by number and rain volume occur near the median though, with a slight tendency for the TMI* to be greater than the PR for features with ice scattering (b) (the opposite is true for features NI in c). A similar pattern is seen over ocean in (d-f), with a slight tendency for more WI features to have TMI* > PR above the 90th percentile.

The geographic locations of the 200 features over land and 200 features over ocean with the highest values of TMI*-PR and PR-TMI* volumetric rainfall by feature type appears in Fig. 51. The locations of MCSs with greatest TMI*-PR (a) are generally located in areas that see large rain amounts from MCSs, in agreement with the previous finding that TMI* generally overestimates for MCSs. However, the locations of MCSs with greatest PR-TMI* is confined mostly to the mid-latitudes and low rain areas (i.e., Saudi Arabia). The same patterns hold for PFs WI for features with large PR-TMI*, being mostly confined to mid-latitudes. However, features WI with large TMI*-PR are more heavily weighted to mid-latitudes both over land and ocean. Note the lack of extreme disagreement over the low latitude oceans. For features without ice
Figure 51. Locations of the 200 features over land and ocean with the largest absolute differences between the PR and TMI estimates by PF type. Each panel shows (a) MCSs, (b) PFs WI, and (c) PFs NI.
scattering, there is a concentration of features with estimates disagreeing in both directions along the coastlines. This suggests that coastline errors in the TMI* algorithm may act in both a positive and negative direction with respect to the PR estimates. However, there is still a scatter of disagreements in both directions over the midlatitudes and the continents in general, with a lack of such features over the low latitude oceans.

Fig. 52 shows the geographic location of the features with the largest fractional difference between TMI and PR relative to the PR estimates. This technique provides the advantage over the previous figure that it can detect disagreements for small rain volume features, giving a better indication of possible artifacts. For MCSs (a), we see that the highest TMI biases fractionally occur in the high terrain of the Andes and Himalayas over land, over ocean there are clusters over the east Pacific ITCZ (Berg and Kummerow 2002), the Pacific Warm Pool, and the midlatitude Pacific storm track. Mountainous areas over land are also the locations of many high fractional disagreements for features with ice scattering (b), indicating the presence of artifacts. Coastlines also tend to contain a number of features with disagreements in both directions. For features without ice scattering, there is again a focus of features with extreme fractional TMI*->PR values towards the mid-latitudes and coastlines, however there are also a number of features over the tropical continents meeting these criteria as well. Features with extreme PR->TMI* occur fairly uniformly, however there are concentrations of features along the South American and Indian coastlines. In both Figs. 51 and 52, there are several regions containing features of the same type with biases in both directions (e.g., the southern US and Amazon in Fig. 51a).
Figure 52. Locations of the 200 features over land and ocean with the largest values fractional differences between the PR and TMI* estimates by PF type. Each panel shows (a) MCSs, (b) PFs WI, and (c) PFs NI.
Examples of PFs with Disagreeing Estimates

To illustrate some of these algorithm disagreements, four examples of precipitation features rain estimates, as well as ancillary observations from TRMM are presented. Fig. 53 shows a typical MCS over the Amazon as seen by three of the TRMM instruments on April 4, 2002. The TMI 85 GHz PCT and the NESDIS operational algorithm described above, are shown in panel (a) and (b), respectively. They show considerable ice scattering depressions at 85 GHz down to 125 K, coincident with heavy rain rates from the NESDIS algorithm. The Visible and Infrared Scanner (VIRS) 10.7 µm brightness temperatures (c) show cloud top temperatures less than −75°C, indicating deep convection. The PR near surface reflectivity field (d) shows a convective line on the west side of the system, with a trailing stratiform region to the southeast. The 2A12 TMI and 2A25 PR rain fields are shown in panels (e) and (f) respectively. There is general agreement in the spatial pattern of the TMI and PR estimates, however there are several of the aforementioned bias characteristics that occur in this storm that lead to the TMI estimate being 43% higher than the PR’s. The rain rates in the convective regions are similar (35-45 mm hr\(^{-1}\)), however, the TMI’s rain rate in the stratiform region is 10-15 mm hr\(^{-1}\) where the PR’s rain rate (and the NESDIS version of the algorithm) is often times less than 5 mm hr\(^{-1}\). In addition, there appears to be an artifact along the edge of the rainfall area in the TMI estimate, where occasionally a 15 mm hr\(^{-1}\) pixel is selected from the database even though there is no enhanced scattering at 85 GHz. Both of these effects are commonly observed in PFs and often lead to a systematic overestimation in the stratiform regions of convective systems. It is interesting to note, however, that the TMI’s rain volume estimate (283911
Figure 53. TMI, PR, and VIRS observations of an MCS over the Amazon on April 4, 2002. Each panel shows (a) TMI 85 GHz PCT (shaded, K), (b) NESDIS rainfall (shaded, mm hr\(^{-1}\)) and 21 GHz vertical polarization \(T_b\) (contoured at 255, 262, and 269 K; 262 K is thick), (c) VIRS 10.7 \(\mu\)m \(T_b\) (K, shaded), (d) TMI 2A12 rainfall (shaded, mm hr\(^{-1}\)), and (e) PR 2A25 rainfall (shaded, mm hr\(^{-1}\)).
mm hr⁻¹ km²) is 43% higher than the PR’s (198434 mm hr⁻¹ km²); the NESDIS algorithm’s estimate (273043 mm hr⁻¹ km²) is only slightly closer to the PR’s (37.6% higher).

The second example (Fig. 54) illustrates the coastline artifact in the TMI rainfall estimates in an MCS near the US Gulf Coast on March 1, 2002. The 85 GHz ice scattering signatures (a) show a large ice scattering area straddling the Louisiana coast; the NESDIS algorithm (b) estimates rainfall, sometimes heavy, in the same regions. Minimum VIRS cloud top temperatures (c) are around −75°C near the region of most intense ice scattering. The PR near surface reflectivities exceed 55 dBZ in the convective regions of the systems, with very intense reflectivities in the stratiform region exceeding 40 dBZ. The TMI (d) and PR (e) rain fields are quite different in this case. The region of intense convection is handled fairly well by the TMI over-ocean algorithm, although peak rain rates are somewhat less than the PR’s. However, there are some discontinuities in the rain field that appear as boxes in the stratiform region, which is caused by the coastline mask in the TMI algorithm. This causes the PR to overestimate (by 13%) with respect to the TMI in this case, due partially to the lower rain rates along the coast. Other cases (not shown) that make the TMI greater than the PR along coastlines are not shown.

The third example (Fig. 55) shows an MCS over the southern Mississippi Valley on March 31, 2002. A region of ice scattering at 85 GHz (a) is apparent; the NESDIS algorithm produces a cold frontal-like structure in the region. Minimum cloud top temperatures from VIRS (c) are only between -65 and -70°C; however PR near surface reflectivities (d) are high in both the convective and stratiform regions. However the
Figure 54. TMI, PR, and VIRS observations of an MCS over the US Gulf Coast on March 1, 2002. Each panel shows (a) TMI 85 GHz PCT (shaded, K), (b) NESDIS rainfall (shaded, mm hr$^{-1}$) and 21 GHz vertical polarization $T_b$ (contoured at 255, 262, and 269 K; 262 K is thick), (c) VIRS 10.7 μm $T_b$ (K, shaded), (d) TMI 2A12 rainfall (shaded, mm hr$^{-1}$), and (e) PR 2A25 rainfall (shaded, mm hr$^{-1}$).
Figure 55. TMI, PR, and VIRS observations of an MCS over the Mississippi Valley on March 31, 2002. Each panel shows (a) TMI 85 GHz PCT (shaded, K), (b) NESDIS rainfall (shaded, mm hr$^{-1}$) and 21 GHz vertical polarization $T_b$ (contoured at 255, 262, and 269 K; 262 K is thick), (c) VIRS 10.7 µm $T_b$ (K, shaded), (d) TMI 2A12 rainfall (shaded, mm hr$^{-1}$), and (e) PR 2A25 rainfall (shaded, mm hr$^{-1}$).
TMI rain (e) field shows very little convective rainfall, in addition the stratiform rainfall appears areally truncated when compared with the NESDIS algorithm (b) and PR (f). It was found that the TMI algorithm has a snow screen whereby 21 GHz brightness temperatures less than 262 K are classified as snow (J. McCollum, personal communication). In this case, however, high values of soil moisture were responsible for the depression at 21 GHz (b), setting the TMI rainfall to zero in that case. It is possible that the lower seasonal TMI rainfall values in the Mississippi River basin (see Fig. 24), when compared to the other instruments, are due to this effect. The scope of this problem globally is a topic for future research.

The fourth example (Fig. 56) shows an area of 85 GHz ice scattering (a) and NESDIS-estimated rainfall (b) in the Zagros Mountains in Iran on April 2, 2002. Cloud top temperatures (c) range down to between -65 and -70°C, and the PR near surface reflectivity field (d) indicates some embedded convection in a large rain area. However, the 21 GHz threshold is triggered (b) likely from snow cover or otherwise radiometrically cold surface in the mountains, and the 2A12 rain (e) is set to zero in these regions, the NESDIS (b) PR estimate (f) appears reasonable in this case. The problem of snow cover (and varying surface emissivity) in the version 5 products leads to many of the differing estimates in the mid-latitudes in particular. These issues will need to be addressed, with an algorithm that uses a variable emissivity threshold, in order to estimate precipitation in areas of high soil moisture and variable snow cover.
Figure 56. TMI, PR, and VIRS observations of an MCS over the Zagros Mountains on April 2, 2002. Each panel shows (a) TMI 85 GHz PCT (shaded, K), (b) NESDIS rainfall (shaded, mm hr⁻¹) and 21 GHz vertical polarization $T_b$ (contoured at 255, 262, and 269 K; 262 K is thick), (c) VIRS 10.7 $\mu$m $T_b$ (K, shaded), (d) TMI 2A12 rainfall (shaded, mm hr⁻¹), and (e) PR 2A25 rainfall (shaded, mm hr⁻¹).
Summary and Discussion

This study shows that the TRMM PR and TMI rainfall estimates agree within 25% tropics-wide (cf. Kummerow et al. 2001, Masunaga 2002), and these estimates agree within 20% tropics-wide when compared the GPCC gauge networks in locations with at least two gauges in a 2.5° grid box. The TMI was shown to be, on average, 18% higher than the GPCC gauges in these locations, with the PR less than the gauges by 8%. However, it is emphasized that significant regional, seasonal, and storm type biases exist among the version 5 TRMM PR and TMI products, GPCC and CPC gauge products, and other rainfall estimates, often exceeding 100% on a seasonal and regional basis. However, the paucity of GPCC gauge stations in the deep tropics in particular must be taken into account in understanding quantitative remote sensing-GPCC gauge comparisons in many gauge sparse regions (e.g., central Africa), as well as effects of terrain, as these introduce significant interpolation biases as well as random errors in the gauge network estimates. In addition, significant coastline and cold surface screening artifacts remain in the TMI algorithm. These artifacts have a significant effect on TMI rain estimates on a regional and seasonal basis and must be accounted for in examining the TMI estimates.

In comparing four years of tropics-wide estimates, the TMI estimates are generally higher than those from the PR and GPCC in the deep tropics and during the warm seasons in mid-latitude locations. This is in agreement with the result of Masunaga et al. (2002), who find that TMI near surface precipitation water content values at low latitudes are higher than the PR’s; however, their study links this difference to a bias in the PR’s attenuation correction causing low rain rates. This study
finds that the PR rain rates are much more in agreement with the GPCC gauge reports than the TMI’s; the TMI rain algorithm is biased high with respect to the other estimates in the deep tropics. During the cold seasons in midlatitudes, PR estimates generally tended to be closer to, or higher than, the TMI and gauge estimates. This is in agreement with Masunaga et al. (2002), who find that the PR retrievals of near surface precipitation water content are higher than the TMI’s.

Despite the zonal trends mentioned, there are important regional variations due to genuine variability in the cloud systems causing the differences and the surface artifacts in the TMI algorithm. Many areas during their warm and transition seasons where MCSs dominate the rainfall budget (i.e., the Southern Plains of the US, Subtropical South America, and equatorial Africa) and mountainous and dry regions have areas where the PR estimates are higher than the gauges and the TMI. Over eastern China, the gauge estimates are almost always higher than the PR and TMI retrievals, despite a strongly seasonally dependent rainfall regime, likely due to the low fraction of rainfall from MCSs and the dominance of frontal rainfall. A detailed examination of the estimates over the US revealed that there are high biases by both the PR and TMI in most rainy regions in the southeast, in agreement with the findings of McCollum et al. (2002). Some of the TMI positive bias in the US is due to an actual rain retrieval bias; however, cold surface and coastline effects affect retrievals over the western and the southeast US in winter and summer, respectively. In addition, overestimates by the PR and, to a lesser extent, the TMI with respect to the gauges, occur in areas with a high fraction of rainfall from MCSs. This is hypothesized to be caused by a sampling problem due to the narrow swath of the PR and serial sampling in
midlatitudes. This is corroborated by the finding that the TMI almost always overestimates relative to the PR for MCSs on a system-by-system basis. This PR overestimate was often serious on a subcontinental scale, and this PR overestimate is included in its zonal averages at midlatitudes. This was shown to be the case seasonally in relating the overestimates to the seasonally varying contribution to rainfall in midlatitude regions versus tropical regions, where the former locations have the sampling problem and PR > TMI > gauge rainfall in seasons where the rainfall budget is MCS-dominated. The scope and exact cause of this apparent sampling artifact remain a topic for further study.

When examining the rain rate biases by feature type, normalizing for sampling differences between the PR and TMI swaths by examining only the TMI retrievals within the PR swath (called TMI*), the TMI* overestimates tropics-wide rainfall from MCSs with respect to the PR by 49% and 53% over land and ocean, respectively, and by 10% and 31% for features WI over land and ocean, respectively. The PR was higher than the TMI* for features NI, by 17% and 54% over land and ocean, respectively. Note that the biases here do not add to 100% because of a nonuniform partitioning of rainfall by system type. Using the PR convective-stratiform separation, globally over land the ratio of convective to stratiform rainfall for the PR is about 60:40, with about a half of a percent of the rainfall not classified as convective or stratiform. For the TMI in the same pixels, the convective-stratiform ratio becomes 27%:52%, with 22% of the TMI* rain falling outside of the PR’s convective and stratiform areas; this difference is due to the spreading of “convective” ice scattering signatures outside the convective PR pixels and pixel mismatching due to scan geometry.
Despite the mismatch in the observations, however, the PR and TMI* mean conditional rain rates and their histograms in the PR-classified convective regions were comparable (only slightly underestimated by the TMI*), especially in MCSs and features WI. On the other hand, TMI* stratiform rain rates were factors of 1.5 to nearly 3 higher than the PR for MCSs and features WI over both land and ocean; the TMI*’s rain rate histograms were biased towards higher rain rates as well. The overestimates in the stratiform regions lead largely to the positive biases seen in the TMI* estimates where MCSs and features were present, with convective rain amounts more comparable. Rain rates for features NI were underestimated from the TMI* with respect to the PR due largely to sensitivity and beam filling considerations, and regions where they are the more dominant in the rain budget (i.e., the stratocumulus regions of the ocean) saw their rainfall underestimated from the TMI*.

When examining the estimates on a feature-by-feature basis, the distributions of the biases by system type can be evaluated as a function of rain volume and feature location. Rainfall from MCSs over land and ocean are almost always overestimated by the TMI* with respect to the PR, due to the overestimate of their stratiform (and “other” rain components, and also differences in instrument resolution. This occurs to an extreme over land, but occurs over ocean even where a convective-stratiform algorithm is used. For heavier raining features WI, the same overestimation by the TMI* occurs. However, for smaller rain volume features WI and features NI, sensitivity and beam filling issues from the TMI dominate, especially over the ocean, leading to PR estimates being higher than the TMI*’s for features with small rain volumes. The geographic locations of PFs with the highest absolute TMI* positive bias were found in rainy
regions, and along coastlines, whereas PFs where the PR was biased the highest were mostly in the midlatitudes. Areas with the highest TMI* > PR fractional differences for MCSs and features WI indicated land areas where artifacts likely exist: over higher elevations and deserts. PR high fractional differences for these feature types over ocean occurred in the East Pacific and Warm Pool, as well as the Southern Hemisphere midlatitude storm track (in agreement with the TMI* overestimation hypotheses discussed above).

The implications of these results point to several key issues that should be considered in future study, validation, and rainfall algorithm development. The first, and most important result, is that it has been shown that the rainfall estimate biases must be evaluated as a function of rainfall regime on a regional and seasonal basis. Simply integrating the biases on a zonal basis hides many of the disagreements between algorithms, and also hides useful information that can yield insights into the causes of the disagreements. With the reprocessing of the “version 6” TRMM algorithms planned for early 2003, a coincident production of a 1997-present PF database will yield a powerful tool to further investigate these regional and seasonal biases.

This study has shown that rainfall biases are a function of PF type over both land and ocean. Since there are characteristic differences in the structures, radiative signatures, and biases by feature type, this information might be used to construct a “smarter” microwave algorithm which uses the physical attributes to limit its selection of profiles to features in a model database with similar structure and radiative characteristics. To some extent, this can be accomplished by a stratiform-convective separation (which will be included over land in version 6, McCollum and Ferraro
2002), but further information such as the ice scattering intensity, “PF type”, or other characteristics should be useful in constraining the observed radiances with a proper model simulation that represents the pixel scene more properly. The misassignment of rainfall to the improper feature types also has implications on the retrieval of the heating profiles associated with the systems in a given region. The partitioning of rainfall into the proper rainfall regime in a particular location is crucial to properly assigning that regime’s characteristic heating profile. In a given region, the high positive bias of the TMI with respect to the PR for MCSs and features WI and the negative bias for features with NI causes a shift of the rainfall budget in a given region towards those systems with the positive bias, and thus the retrieved latent heating estimate (in algorithms which use convective-stratiform information as input) would be biased from the “typical” heating profile toward the types of systems that have the positive bias. So this issue not only has implications on rainfall biases, but also the heating profile biases that are caused as a result.

Secondly, satellite validation efforts must produce a coincident product that can be quantitatively compared to the satellite algorithms, and placed in the proper context of the satellite dataset. Both the PR and TMI have significant biases with respect to the GPCC gauge networks. However, quantitative comparisons with gauge networks must include significant random error considerations. Satellite validation efforts from the planned Global Precipitation Mission must focus on creating datasets that can more directly and quantitatively be compared to the satellite observations, and be able to more directly validate the assumptions of the algorithms. This must be focused on particular observed storm types in a given region. For the PR, this should include a
wider validation of the crucial DSD assumption and attenuation correction methods. For the TMI, techniques to constrain observed parameter space of hydrometeor phases, mixing ratios, size distributions, and densities must done in the liquid, the mixed-phase, and the ice region, not only to improve the retrievals but also the cloud models that simulate them. Some of this information may be gleaned from existing datasets, but more quantitative observational comparisons must be developed in order for our conceptual and numerical models to be improved to better represent the water budgets of precipitating systems.
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