Long-Term Comparison of Collocated Instantaneous Rain Retrievals from the TRMM Microwave Imager and Precipitation Radar over the Ocean

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(Manuscript received 10 September 2014, in final form 14 January 2015)

ABSTRACT
Version-7 (V7) rain rates retrieved by the TRMM Microwave Imager (TMI) and Precipitation Radar (PR) are spatially and temporally collocated over the ocean and compared at TMI footprint scale for the summer months of 16 years, within the TRMM coverage belt from 38°S to 38°N latitude. This study puts special emphasis on examining how the estimates from the two instruments compare with each other for different rain types and for different geographical locations. It is found that, although the two rain-rate estimates agree with each other extremely well (only 2.6% difference) when averaged globally and over all rain types, large discrepancies (>60%) are observed if comparisons are conducted for rain pixels of only convective type or for regions where convective rain types dominate. For the stratiform rain type, the TMI and PR retrievals compare well with a difference of ~13% globally. In particular, the partial beam filling seems to be less important to the underestimation of TMI rain against PR rain than the spatial variability of rain. These findings point to the existing need for better understanding of the remote-sensing physics of convective rain. Such an improved understanding is critically important to decreasing the uncertainty in oceanic rainfall estimation from space in the coming GPM era of global long-term observations that will lead to the creation of a climate record of trends in precipitation.

1. Introduction
The Tropical Rainfall Measuring Mission (TRMM) is the first spaceborne mission to observe the 3D distribution of rainfall between 38°S and 38°N (Simpson et al. 1988; Kummerow et al. 1998). It was launched in late 1997 and has been collecting precipitation data since. The exceptional performance of the precipitation-observing instruments onboard TRMM has provided an invaluable amount of data. The detailed record of precipitation observations of 16+ years allows, for the first time, the possibility to study rain-related climatology. One of the most valuable benefits that the TRMM mission has provided is the set of coincident rainfall estimations that come from two independent rainfall measurements provided by two very different, independent instruments—the TRMM Microwave Imager (TMI) and Precipitation Radar (PR). These complementary observations have allowed us to better understand the rainfall characteristics and resulted in a significant decrease of the uncertainty in space-based rainfall estimates. Building upon the successful heritage of TRMM, the Global Precipitation Measurement...
(GPM) Core Observatory satellite was launched by the National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) on 27 February 2014, carrying an advanced microwave radiometer and a dual-frequency radar.

The latest version-7 (V7) TRMM retrievals show a better comparison between the PR and TMI rain estimates, especially over land, relative to the discrepancies found in the version-6 (V6) products (e.g., Seto et al. 2011). Despite all the improvements in rainfall retrieval over the last couple of decades, there is still disagreement between the estimates from different instruments and different retrieval algorithms (e.g., Kummerow et al. 2001; Nesbitt et al. 2004; Yuter et al. 2006; Bowman 2005; Seo et al. 2007b; Shige et al. 2006, 2008; Wolff and Fisher 2008), depending on the assumptions that they employ (e.g., Kummerow et al. 2001; Olson et al. 2006). Hence, it is very important to carefully characterize the state-of-the-art rainfall retrievals from each of the two instruments in order to improve our understanding of the two measurements in preparation for the new GPM era.

A number of previous studies have performed a variety of comparisons. However, they often focused on comparing the statistics of the two independent estimates, aggregated separately on, in general, $0.5^\circ \times 0.5^\circ$ resolution grids and accumulated on monthly, seasonal, and annual time scales over limited periods of TRMM observations and sometimes over specific regions (e.g., Berg et al. 2002, 2006; Shige et al. 2006, 2008; Wolff and Fisher 2008). For example, Berg et al. (2006) showed the relationship of the TMI and PR intensity ratio against the column water vapor, and Shige et al. (2008) utilized a radiative transfer model to infer the cause for the large underestimation of the PR-derived rain in the eastern Pacific Ocean. They concluded that the discrepancy can be attributed to the presence of more small-to-medium sized raindrops in the eastern Pacific than in the western Pacific Ocean and the associated difficulty in detecting them with PR given its sensitivity. While providing useful information about the uncertainty of the estimates, such types of studies using averaged statistics often mask the underlying physics for the observed discrepancies.

In this light, of particular interest are the studies by Seo et al. (2007b) and Wolff and Fisher (2008), who focused on the comparison of instantaneous rain-rate estimates at the scale of the TMI nominal footprint instead on time- and space-aggregated means. Such approaches are indeed much more desired for better understanding of the remote-sensing physics of rainfall. The former study used 1 yr of TRMM global observations over the oceans. It showed that the difference between the V6 TMI and PR rain rate is a function of rain intensity and rain type. By focusing on comparing satellite retrievals (V6 TMI and PR) to retrievals from ground-based radars, the latter study was naturally limited to only two places around the globe that were selected as ground validation (GV) sites. Hence, both results might exhibit additional dependence on geographical region and climatology and would become more robust with the long-term dataset of the latest version of TRMM retrievals.

Although the V7 TMI and PR algorithms serve as the bases for the GPM rainfall algorithm, their products have not been extensively compared or evaluated yet except for zonal-mean rainfall comparison over the ocean and instantaneous rainfall comparison over land between the PR and TMI rain (e.g., Kummerow et al. 2011; Gopalan et al. 2010).

In this study, we adopt the approach of Seo et al. (2007b) and compare instantaneous TMI and PR rain rates after first collocating them in space and time over the ocean and bringing them to the same horizontal scale. By using only collocated observations we avoid the impact of the different sampling as introduced by the different swath coverage of the two instruments. Using this approach, we can better understand and cross check the long-term behavior of the two different rainfall retrievals. Here, we greatly extend the scope of the previous studies by performing the comparison over the entire period (16+ yr) of TRMM summertime observations and over the global oceans observed by TRMM. Furthermore, we examine the statistics of the TMI and PR comparison by rain type (convective vs stratiform) globally as well as regionally.

This study comes at a time when we need a detailed evaluation of the performance of the current TRMM algorithms to understand the sources of the discrepancy between estimates from different instruments and retrievals. Such knowledge will provide guidance in developing new approaches and reducing biases in the GPM-era rain estimates from space. It is noted that the retrieval algorithms for GPM core satellite are different from the TRMM algorithms. Therefore, the results from this study may not be directly implemented in the new algorithms, although they may still be used as guidelines for improving algorithm physics.

2. Data and study method

Datasets used in this study are the V7 products of TMI- and PR-derived rain rates over oceanic regions for June–August for the Northern Hemisphere and December–February for the Southern Hemisphere from 1997 to 2013. We focus on summertime precipitation in each of the two hemispheres in order to exclude periods with possible snowfall since those retrievals are more uncertain.
The PR is a cross-track scanning radar operating at 13.8 GHz (Iguchi and Meneghini 1994). Its sensitivity is about 17 dBZ, which corresponds to about 0.7 mm h\(^{-1}\) in rain rate. PR pixels have a horizontal resolution of 5.0 km at nadir after the orbit boost of the TRMM satellite in August 2001. The PR observations and rainfall estimates near the surface are further classified into three types: stratiform, convective, and others (Awaka et al. 1998).

TMI is a conically scanning radiometer. The TMI-derived rain rate represents an averaged value at a nominal footprint area of 18 km \(\times\) 18 km (e.g., Olson et al. 2006; Kummerow et al. 2011). The TMI rain retrieval algorithm approach has been documented by Kummerow et al. (2000, 2001). However, the retrieval database has been modified recently. In particular, the V7 TMI algorithm uses an observationally constrained database that is constructed using the PR and TMI measurements (Kummerow et al. 2011). Because the database contains the observed proportions of raining and nonraining pixels, no a priori decision is made regarding the rain status of a given pixel prior to the rain retrieval. Hence, a threshold of minimum possible rain rate needs to be determined for collocating TMI and PR rain pixels.

To collocate TMI and PR rain pixels, we focus on a subset of TMI observations that contain only the 12 TMI pixels around the center of the TMI swath to get a better geometry match between the two measurements (avoiding PR observations that are too far off nadir). The swath width of the 12 TMI pixels corresponds to about 90 km. For each of these TMI pixels, we compute the distance between the center of the TMI pixel and the set of PR observations that are in a close proximity. We then select only those PR pixels that fall within the 19-GHz TMI field of view (FOV) and convolve their corresponding PR rain rates using the 19-GHz antenna gain function to represent the averaged PR rain rate over the TMI footprint scale. In this collocation process, about 15 PR pixels are commonly found in the nominal TMI footprint. Hereinafter, the PR-derived rain rate implies the averaged (or convolved) one over this nominal footprint. The statistics in the comparison between the two measurements might be affected by the boost effect due to the change of the TMI and PR pixel sizes and the reduction of sensitivity to rain. However, the effect might not be significant in the TMI nominal footprint scale since after the convolution procedure results in the same collocated areas of TMI and PR (aggregated from original PR pixels). Previously, we checked the rain retrievals from the two measurements in a different nominal footprint scale. The main results did not change.

Among the collocated observations, we chose for comparison only oceanic pixels whose TMI-derived rain rates or PR-derived rain rates are greater than 0.05 mm h\(^{-1}\). Theoretically, the possible minimum PR detectable rain rate for a given collocated footprint is around 0.05 mm h\(^{-1}\), considering the situation when only one subpixel out of the ~15 collocated PR subpixels has rain with a rate of ~0.7 mm h\(^{-1}\), which corresponds to the minimum detectable dBZ. So, the criterion for selecting rainy pixels, that is, >0.05 mm h\(^{-1}\), seems to be conservative when taking into account the TMI and PR detectable rain intensities (C. Kummerow 2011, personal communication). Based on the chosen dataset, the TMI pixels with PR-derived rain rates < 0.05 mm h\(^{-1}\) amount to 8.5% of the total TMI rain, while the PR rainy pixels with TMI-derived rain rates < 0.05 mm h\(^{-1}\) amount to 2.8% of the total PR rain.

To identify rain types of the collocated pixels, we use the convective (stratiform) areal fraction convF (stratF), which is defined as the ratio of the number of convective (stratiform) PR pixels given by 2A23 products to the total number of collocated PR pixels within the TMI footprint. For PR rain types, we use all range of convective (rainType = \(~200–299\) and stratiform (rainType = \(~100–199\) rain types regardless of their classification, such as “certain,” “maybe,” “shallow,” or “isolated.” Based on these areal fractions, rain pixels at the TMI footprint scale are classified into one of the following four categories:

\[
\text{category} = \begin{cases} 
1(\text{convective}) & \text{convF} \geq 0.5 \\
2(\text{stratiform}) & \text{stratF} \geq 0.5 \\
3(\text{mixed}) & \left\{ \begin{array}{l}
\text{convF} < 0.5 \\
\text{except convF} = 0 \\ 
\text{and stratF} = 0
\end{array} \right. \\
4(\text{residual}) & \left\{ \begin{array}{l}
\text{convF} = 0 \\
\text{and stratF} = 0
\end{array} \right.
\end{cases}
\]

Accordingly, categories 1 and 2 constitute mostly convective and mostly stratiform rain, respectively. Category 3 has a mixture of convective and stratiform rain, which is referred to as “mixed” hereinafter. Finally, a fourth category is “residual,” which has rain (either by PR or by TMI), but no rain type information is given in the 2A23 product. (Note that “no rain type” information in 2A23 is designated as “others.”) To clarify,
Table 1. Statistics of global TMI and PR rain rates as a function of rain types.

<table>
<thead>
<tr>
<th></th>
<th>Convective</th>
<th>Stratiform</th>
<th>Mixed</th>
<th>Residual</th>
<th>All types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency by pixel number (%)</td>
<td>1.44</td>
<td>15.44</td>
<td>54.64</td>
<td>28.48</td>
<td>100</td>
</tr>
<tr>
<td>PR fraction by total PR rain (%)</td>
<td>16.14</td>
<td>49.57</td>
<td>33.94</td>
<td>0.01</td>
<td>100</td>
</tr>
<tr>
<td>TMI fraction by total TMI rain (%)</td>
<td>8.31</td>
<td>55.31</td>
<td>30.12</td>
<td>3.25</td>
<td>100</td>
</tr>
<tr>
<td>Mean PR rain rate (mm h⁻¹)</td>
<td>8.55</td>
<td>2.45</td>
<td>0.47</td>
<td>0.00</td>
<td>0.76</td>
</tr>
<tr>
<td>Mean TMI rain rate (mm h⁻¹)</td>
<td>4.49</td>
<td>2.78</td>
<td>0.43</td>
<td>0.16</td>
<td>0.78</td>
</tr>
<tr>
<td>TMI − PR (mm h⁻¹)</td>
<td>−4.06</td>
<td>0.33</td>
<td>−0.04</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>(TMI − PR)/[0.5 × (TMI + PR)] (%)</td>
<td>−62.27</td>
<td>12.62</td>
<td>−8.89</td>
<td>200.00</td>
<td>2.60</td>
</tr>
</tbody>
</table>

3. TMI and PR rain

Using the 16-yr collocated rain pixels, we compared the TMI- and PR-derived instantaneous rain in terms of rain types and furthermore examined their regional and/or weather regime dependence in the TRMM-covered globe.

a. Frequency distributions of rain intensity

Based on the criterion of the rain type classification, 1.44%, 15.44%, and 54.64% of the 16-yr global rain pixels are assigned to convective, stratiform, and mixed rain, respectively (Table 1), while 28.48% remain in the category of residual (no rain type designated by PR). For the convective rain type, the frequency of 1.44% in the TMI footprint scale seems to be very small compared to the frequency in the PR footprint scale, which has sea-level proportions. The TMI footprint scale seems to be very small compared to the total TMI rain amount. The fraction is quite large relative to ~0% of the total PR rain amount. This can be attributed partly to the limitations in the TMI/PR rain detection (the limitations being possibly more pronounced for the PR). Note that the fraction by the residual rain type can slightly change when we choose a threshold other than 0.05 mm h⁻¹ used in this study.

In contrast, the contributions of the different rain types to the total TMI rain amount are quite different. The fraction of the convective TMI rain to the total TMI rain amount is only a half of that for PR (~8% for TMI vs ~16% for PR), while the stratiform TMI rain amount fraction is larger than the corresponding PR fraction (~55% for TMI vs ~50% for PR). These results indicate a relative underestimation and overestimation of the TMI rain in the convective and stratiform rain types, respectively, compared to the PR rain. This is further explored in the following results.

In addition, the residual TMI rain contributes about 3% to the total TMI rain amount. The fraction is quite large relative to ~0% of the total PR rain amount. This can be attributed partly to the limitations in the TMI/PR rain detection (the limitations being possibly more pronounced for the PR). Note that the fraction by the residual rain type can slightly change when we choose a threshold other than 0.05 mm h⁻¹ used in this study.

On average, rainy pixels produce rain intensity of 0.78 and 0.76 mm h⁻¹ for TMI and PR observations, respectively, resulting in a relatively very small difference of 2.60% between the two independent measurements, when compared globally and over all rain types. Note that the difference in Table 1 implies how different the TMI and PR rain rates are, no matter which one is valid (here we use the average of the two when calculating percentage difference). This difference is much smaller compared to the results from the previous studies (from...
Mean TMI and PR rain rates for convective rain clouds when PR rain rate > a given threshold.

<table>
<thead>
<tr>
<th>PR &gt; 1 mm h(^{-1})</th>
<th>PR &gt; 5 mm h(^{-1})</th>
<th>PR &gt; 10 mm h(^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean PR rain rate (mm h(^{-1}))</td>
<td>8.73</td>
<td>12.52</td>
</tr>
<tr>
<td>Mean TMI rain rate (mm h(^{-1}))</td>
<td>4.57</td>
<td>6.39</td>
</tr>
<tr>
<td>TMI – PR (mm h(^{-1}))</td>
<td>−4.16</td>
<td>−6.13</td>
</tr>
<tr>
<td>(TMI – PR)[0.5 × (TMI + PR)] (%)</td>
<td>−62.56</td>
<td>−64.83</td>
</tr>
</tbody>
</table>

previous versions of the algorithms) when comparing accumulated TMI and PR rain amounts (e.g., Kummerow et al. 2000; 2001; Yuter et al. 2005; Shige et al. 2006; 2008; Seo et al. 2007b; Wolff and Fisher 2008). In this aspect, the TMI and PR V7 algorithms have made substantial progress in decreasing the uncertainty in retrieving global rainfall, compared to the V6 algorithms.

Mean rain intensity is examined further for each rain type (Table 1). The mean stratiform rain rates are 2.78 and 2.45 mm h\(^{-1}\), respectively, for TMI and PR, showing a good agreement (12.62% difference). For the rain type of mixed, the mean TMI and PR rain rates are 0.43 and 0.47 mm h\(^{-1}\), yielding an 8.89% difference. However, for convective rain types, they are 4.49 and 8.55 mm h\(^{-1}\), respectively, having a 62.27% difference. In particular, convective rain exhibits a negative sign as well as a large value in the TMI minus PR (TMI – PR) rain rates, which indicates that TMI rain retrieval is considerably lower relative to PR rain retrieval. Meanwhile, the large difference can be due to a large number of very light TMI rain rate, resulting in the small mean rain intensity for the TMI rain. To exclude the influence of the very light TMI rain (related to the limitations in the TMI/PR rain detection) on the mean rain intensity, we chose PR rain thresholds such as 1, 5, and 10 mm h\(^{-1}\) and perform the comparison again after excluding all rain rates lower than the thresholds. Nevertheless, the differences between the mean TMI and PR rain rates remain very large and are comparable to the original 62.27% (Table 2). A similar result pointing to the TMI rain relative underestimation can be found in Zagrodnik and Jiang (2013). They showed that the PR 2A25 produces larger mean rain rates than the TMI 2A12 in the inner cores and inner bands of hurricanes, which are mostly composed of convective clouds. The class of mixed also shows relative underestimation by TMI (a negative sign in the TMI – PR rain difference). Unlike convective and mixed rain types, stratiform rain shows a positive difference.

To investigate the discrepancies, the joint probability density function (PDF) of the TMI and PR rain-rate distribution is shown in Fig. 1. Note that the rain rate in Fig. 1 is in a logarithmic scale. The solid line is the one-to-one relationship, while the plus signs depict the mean TMI value for each 1 mm h\(^{-1}\) bin of PR, and the triangles depict the mean PR value for each 1 mm h\(^{-1}\) bin in TMI rain. The frequency figure shows a well-balanced cancellation between underestimation and overestimation when all rain types are included (Fig. 1a). For the stratiform and mixed rain types (Figs. 1c,d) there is wide scatter, but it is more or less symmetrically and concentrically distributed along the one-to-one line. However, the convective rain frequency plot (Fig. 1b) shows a rather skewed distribution with greater frequencies occurring below the one-to-one line, resulting in a small mean TMI rain rate relative to the PR mean rain rate. For example, most PR rain intensities in the range of 20 to 40 mm h\(^{-1}\) appear to correspond to TMI rain intensities of approximately 10 mm h\(^{-1}\) or less. The mean TMI value for each PR bin (plus signs in Fig. 1b) reveals a systematic low bias of the TMI rain relative to the PR rain. Although Wolff and Fisher (2008) did not classify the rain types, they found some similar results: while in the low rain-rate regime (in the range of 0 and 20 mm h\(^{-1}\)), there is relatively good correspondence between the TMI, PR, and GV, in the high rain-rate regime (in the range of 21 and 40 mm h\(^{-1}\)), the correspondence is considerably less. In addition, it is reported that the TMI rain intensity greater than 30 mm h\(^{-1}\) is rarely found in the V6 retrievals, and there is a preferred mode in the TMI rain rate distributions at approximately 2 mm h\(^{-1}\), which was not evident in the PR and GV distributions. Our analysis shows that the V7 TMI rain also rarely exceeds 30 mm h\(^{-1}\) (plus signs in Fig. 1b) but does not have any preferred mode around 2 mm h\(^{-1}\).

To illustrate better how the two retrievals compare we computed the mean TMI (PR) rain for each 1 mm h\(^{-1}\) bin of PR (TMI), as noted above. Looking at these mean values for each 1 mm h\(^{-1}\) bin, represented by the plus signs and the triangles in Fig. 1, reveals more detailed features in the relation, showing that the signs of the TMI minus PR rain rate become different at the two ends of the spectrum of rain intensity. For example, relative to binning by PR rain intensity (the plus signs), there is a positive bias at low PR rain intensity (relative overestimation by TMI) and negative bias at relatively high PR rain intensity (relative underestimation by TMI). Interestingly, when binning by TMI intensity (the triangles) we see similar features that are indicating an opposite trend. Namely, at low TMI rain intensity there is a relative overestimation by PR (the triangles are below the one-to-one line), while at high TMI rain intensity there is a relative underestimation by PR (the triangles are above the one-to-one line). In fact, such trends are to...
be expected when computing the mean values of one parameter given a specific range for the other. The explanation is that for values at the extreme ends of the spectrum, it is unlikely that when one of the estimates is there the other one will be there as well. It is much more likely that the dependent estimate will be closer to the mean, resulting in overestimation at the low and an underestimation at the upper end of the independent (control) variable (the one by which the binning is done).

While the over/underestimation at the extreme ends is to be expected, what is interesting to see is how the two types of means (the plus signs and the triangles) relate to the one-to-one line. Ideally, they should be symmetric with respect to that line. Indeed, this seems to be best represented in the comparison for “all rain types” (Fig. 1a), except at the high end, and for the stratiform rain (Fig. 1c), except at the low end. Overall, the TMI and PR rain intensity estimates compare best for the stratiform rain, as illustrated by the highest probability being located concentrically along the one-to-one line and the joint PDF being visually the tightest. However, as pointed out above, it appears that there is a relative TMI overestimation at the low end of the rain intensity spectrum, as manifested by the large population of TMI rain intensity lower than a few millimeters per hour. This seems to explain why the mean value of the TMI stratiform rain (averaged over all intensity ranges) is slightly larger than that of the PR stratiform rain, resulting in a 12.62% difference (Table 1).

The extreme case of relative underestimation by TMI is for the convective rain type (Fig. 1b). In that case, both the triangles and the plus signs lie below the one-to-one
line, while for an unbiased estimate they should be symmetric about that line.

Meanwhile, the comparison for the mixed rain type (Fig. 1d) has the in-between properties of the comparisons for the convective and stratiform rain types. There is an overall tendency for underestimation by TMI (the triangles are very close to the one-to-one line, while the plus signs lie below it). However, as in the case of stratiform rain, it seems that there is a relative TMI overestimation at the low end of the rain intensity spectrum. In other words, for the very light rain (<1 mm h\(^{-1}\)), the TMI shows positive relative bias, similar to the stratiform rain type, while for the rest of the rain intensity ranges it shows a distinct negative relative bias, similar to the convective rain type. Overall, the TMI “mixed rain” type rain has a relative underestimation of 8.89% compared to the PR rain (Table 1).

As a speculation, the serious underestimation of the TMI rain in high rain intensity of PR might be attributed partly to the Bayesian approach, which weighs the a priori database (rain) differently according to the distance from given, observed TMI brightness temperatures (TBs). As mentioned in Seo et al. (2007a), the Bayesian rain retrieval algorithm can suffer from the discontinuous and heavily skewed data distributions of rain rate in the a priori database. Hence, the algorithm tends to easily cause positive bias for very light rain since there are no negative rain-rate values. In addition, it can bring negative bias for very strong rain intensity where many lower-intensity candidates are participating in the weighted mean, while the higher-intensity rain profiles are much rarer because of the natural limitation of the maximum possible rain rate. To avoid the rareness of high rain intensity in the TMI rain retrieval, we might need to narrow the “radius of influence” in the error variance of TB since in the intense rain regime the gradient of rain rate with respect to TB distance is very large.

Another source for the underestimation in V7 might be absence of rain type classification prior to the retrieval. The V7 algorithm uses an a priori database that contains all cloud–radiation relations regardless of the classifications by rain presence and rain type. This strategy might result in the underestimation in convective rain intensity. In general, convective regions are characterized by higher spatial variability, and hence the retrieval of convective rain will be associated with more uncertainty related to the degree of homogeneity inside the satellite FOV (e.g., Hristova-Veleva et al. 2013). The nonlinearity of the relationship between brightness temperatures and rain rate will result in underestimation of rain intensity in the cases when the inhomogeneity is measurable, and this problem is often regarded as nonuniform beam-filling effect.

To investigate how the nonuniform beam-filling effect may have played a role in the difference between TMI and PR retrievals, we computed two parameters, fraction of area and standard deviation of rain rates, within a TMI FOV to represent the inhomogeneity of the rain field. The results are shown in Fig. 2 separately for convective and stratiform rain samples. For the convective and stratiform rain types, the standard deviation of rain rates increases as the rain intensity increases, and the area with a greater value of standard deviation coincides with the area of larger underestimation of TMI against PR, although the magnitude of standard deviation is smaller in stratiform than in convective rain type. The areal fraction of rain within a TMI FOV increases as TMI or PR rain rate increases. Unlike the standard deviation, the areal fraction shows a roughly symmetric distribution along the one-to-one line. Hence, the partial beam filling seems to be less important to the underestimation than the spatial variability of rain. Detecting the degree of inhomogeneity of rain intensity in the observed scene and using appropriate retrieval database will help toward improving the retrievals in the cases of isolated strong convection. Indeed, in a review paper, Stephens and Kummerow (2007) identified several outstanding problems associated with cloud and precipitation retrievals. Two of the three main areas they outlined for future improvements are related to developing the ability to identify the rain presence and to account better for the variability of the atmospheric and surface states in the construction of the databases and during the retrieval.

Overall, the V7 TMI and PR rain retrievals agree very well with each other (only 2.60% difference) when all rain types are combined but exhibit very different behaviors from rain type to rain type and have large discrepancies, in particular, for the convective rain type.

b. Geographical distributions of rain intensity

To study the discrepancies from another angle, in the following we investigate the TMI and PR retrievals at different geographical regions using the 16-yr dataset. Figure 3 presents the spatial distributions of mean rain rates and their differences as a function of rain type, all data were accumulated on a 1° by 1° resolution grid. Overall, both measurements depict well the major wet and dry regions such as the intertropical convergence zone (ITCZ), Indian and Asian monsoons, paths of extratropical cyclones, and the dry southeast Pacific Ocean, while they show quite different distributions in the magnitudes of mean rain intensities. Most convective rain regions show negative values in the TMI − PR difference, implying that the TMI rain rate is systematically lower than the PR rain rate (Fig. 3c). In particular, the large negative differences are found in the wet
regions of ITCZ, monsoon, and extratropical cyclone paths. The regions with positive differences are very rare and most of the regions are located along the edges of dry regions of the northeast and southeast Pacific, southeast Atlantic, and southeast Indian Oceans. These are the areas commonly located along the edges of the well-known, dry, oceanic regions. In these edge areas rain retrieval is also challenging compared to over other regions because of the following reasons: 1) Since the rain intensity in the area is, in general, very low, it is very hard to separate rain versus no-rain pixels. 2) In particular, the southeast Pacific Ocean is well known to produce widespread stratocumulus clouds. These clouds seem to be often detected as rain area by the TMI algorithm, but they can easily be missed by PR (which is limited to detect rain rate below 0.7 mm h\(^{-1}\)). This can be attributed to the overestimation of TMI against PR. 3) The a priori database of the TMI algorithm might not be representative to the rainfall systems occurring in the dry regions. Overall, the convective TMI rain has a clear tendency to be underestimated compared to PR rain in most of the wet regions of the globe.

For stratiform rain, both measurements agree that intense stratiform rain is found mainly in the Asian monsoon regions and along the edges of dry regions in the east Pacific and south Indian Oceans. The difference between the two measurements exhibits quite different geographical distributions from that for convective rain type. Most regions with strong stratiform rain show large positive differences, indicating that the mean TMI rain rate is larger than the mean PR rain rate. The largest positive differences are found in the Asian monsoon regions, extratropical cyclone paths, south Indian Ocean, northeast Pacific Ocean, east ITCZ, and South Pacific convergence zone (SPCZ). In particular, the differences in the Asian monsoon regions show very opposite behaviors for convective and stratiform rain types. That is, both large negative differences for convective and large positive differences for stratiform rain type take place in this region.

Seven regions are selected (marked in Fig. 3) to further investigate the regional dependency of the difference between the TMI and PR rain retrievals, and the results are shown in Table 3 and Fig. 4. Convective pixels...
FIG. 3. The global distribution of (a),(d) mean PR and (b),(e) mean TMI rain rates and (c),(f) TMI minus PR rain rate for convective and stratiform rain types. The rain rates are in millimeters per hour.
Table 3. As in Table 1, except that the statistics of PR and TMI rain rates are shown as a function of rain type, separately for each of the selected regions (marked in Fig. 3). For each region, the first line shows the percent of pixels in this type; the second and third lines represent mean PR and TMI rain intensity, respectively, in mm h$^{-1}$; and the fourth line shows their difference in percent relative to the mean of PR and TMI rain rates. Boldface font indicates numbers that are discussed in the text.

<table>
<thead>
<tr>
<th></th>
<th>Convective</th>
<th>Stratiform</th>
<th>Mixed</th>
<th>Residual</th>
<th>All types</th>
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<td>21.29%</td>
<td>59.80%</td>
<td>17.18%</td>
<td>100%</td>
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<tr>
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<td>2.46</td>
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<td>1.03</td>
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<td>2.59</td>
<td>0.47</td>
<td>0.16</td>
<td>0.94</td>
</tr>
<tr>
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<td>5.15%</td>
<td>$-19.23%$</td>
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<td>$15.91%$</td>
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<td>53.80%</td>
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<td>BEN</td>
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<td>47.33%</td>
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<td>18.99%</td>
<td>$-9.52%$</td>
<td>200.00%</td>
<td>$2.79%$</td>
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<tr>
<td>NEA</td>
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<td>38.91%</td>
<td>25.61%</td>
<td>100%</td>
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</tr>
<tr>
<td></td>
<td>$-52.54%$</td>
<td>32.89%</td>
<td>33.33%</td>
<td>200.00%</td>
<td>$22.37%$</td>
</tr>
</tbody>
</table>

In Bay of Bengal (BEN) occupy 2.87% of all precipitating pixels, occurring 17%–75% more frequently than any other regions. On the other hand, the oceanic areas off the northeastern Asia (NEA) region have the largest stratiform rain frequency (33.07% of all rainy pixels in that region). In terms of convective rain intensity, NEA produces the strongest mean PR rain rate during summer, while the tropical eastern Pacific (EP) generates the weakest mean rain rate at 7.56 mm h$^{-1}$, which is about a half of NEA’s 13.17 mm h$^{-1}$.

For convective rain, the comparison constantly shows negative TMI − PR rain-rate differences in the range of $-65\%$ to $-52\%$ over all the selected regions. For mixed rain, it shows a very wide range of differences between $-19\%$ and 33%. The stratiform rain type exhibits relatively modest differences in the range of 3%–32%. Among the selected regions, the tropical northwestern Pacific (NWP) and the tropical Atlantic Ocean (ATL) have small differences of $-4\%$, while the tropical southwestern Pacific (SWP), EP, the midlatitude NEA, the oceanic regions off subtropical eastern Asia (STEA), and the BEN have differences greater than 10%. Overall, the positive and negative differences due to different rain types largely cancel out each other resulting in a good agreement (2.6% difference) between the two measurements on a global scale.

In particular, the differences between the TMI and PR rain in the NWP and EP regions are examined previously by Berg et al. (2002, 2006) and Shige et al. (2008). Shige et al. (2008) found that the TMI rain is greater than the PR rain over the eastern Pacific, but both rain estimations are in good agreement over the western Pacific. Similar to the previous V5 and V6 TMI algorithms, the latest V7 TMI algorithm also tends to produce more rain than the PR algorithm over the eastern Pacific. On the other hand, the TMI rain shows a relative underestimation over the western Pacific. That is, the EP and NWP regions show opposite signs as well as quite different magnitude in the differences (15.91% vs $-9.13\%$). The opposite signs tend to be led by the mixed rain type, where the TMI rain is overestimated (underestimated) in the EP (NWP) region. The mixed rain type seems to reflect different precipitation characteristics between the two regions. More shallow, stratiform, and light rain is found in the EP region than the NWP region (Berg et al. 2002; Schumacher and Houze 2003; Nesbitt et al. 2006). In addition, convective systems with shorter lifetimes and smaller areas are observed in the EP region (Machado et al. 1998). If so, the FOVs classified as a mixed rain type in EP might be closer to the stratiform rain rather than the convective rain. Accordingly, the TMI rain in the mixed rain type is more readily overestimated in EP. Meanwhile, consideration of its stronger maritime nature (more small to medium sized raindrops)”$^*$ drop size distribution, which was suggested by Shige et al. (2008) to increase the PR rain, might worsen the TMI − PR difference in the eastern Pacific for the convective clouds even though it improves the difference for the stratiform and mixed ones.

In summary, the comparison of instantaneous rain intensity retrieved from TMI and PR measurements shows a good correspondence when computing global statistics. However, a more thorough examination reveals hidden discrepancies that have a strong dependency on rain type and geographical region. Specifically, the discrepancy between the TMI and PR rain retrievals in convective rain type takes place in a systematic way over most TRMM-covered regions. The TMI rain rate is much lower than the PR rain rate for convective rain type. Hence, future improvement efforts should be directed to reconciling the TMI and PR
rain estimates in convective rain type by examining, for example, the partial beam-filling correction in relation to the scale of convective cells.

4. Summary and conclusions

The long-term observations by the two collocated rain-measuring instruments aboard the TRMM satellite (TMI and PR) provide the opportunity to investigate the specifics of the precipitation characteristics and their variation as a function of precipitation type and geographical region. Previous studies often focused on comparing the two estimates in terms of 0.5° grid averages and aggregated on monthly, seasonal, and annual time scales. While these studies provide valuable estimation of the order of uncertainty in the spaceborne precipitation estimates, they cannot provide sufficient insights into the possible sources for the observed discrepancies. To better understand where these differences might be coming from, we focus on analyzing the statistics of spatially and temporally collocated observations over the ocean, circumventing concerns about the different representativeness of the two types of measurements. Indeed, no matter how much efforts are
put into the collocation procedures, there will always be mismatches between the two measurements because of their different scanning geometry, original pixel sizes, and problems related to beam parallax. These mismatches will result in differences between the two retrievals even though the retrieval algorithms for the two sensors are perfect. However, those differences are expected to be “random” in nature.

Our comparison of the V7 rain retrievals from TMI and PR shows a very close correspondence between the two estimates when performing the comparison globally and over all rain types. The decrease of the rain estimation uncertainty is a significant improvement from previous versions of the retrieval algorithms (e.g., Seo et al. 2007b; Wang et al. 2014). However, while the overall mean statistics show remarkably good agreement, a detailed look by rain type and geographical region reveals that many discrepancies still exist. The agreement predominately occurs for convective rain type and over the regions where clouds are mainly convective in nature. In particular, the partial beam filling seems to be less important to the underestimation of TMI rain against PR rain than the spatial variability of rain. These results point to the need for better understanding of the possible sources and taking steps to mitigate the current shortcomings by improving the assumptions used by the different algorithms. This is a critical step that needs to be taken in preparation for the new GPM mission.

Acknowledgments. We acknowledge anonymous reviewers for their constructive comments. This research has been supported by the Korea Meteorological Administration Research and Development Program under Grant CATER 2012–2062 and the research grant of the Kongju National University in 2014.

REFERENCES


