The Varying Response of Microwave Signatures to Different Types of Overland Rainfall Found over the Korean Peninsula

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ABSTRACT

The Tropical Rainfall Measuring Mission (TRMM) precipitation radar and ground rain measurements were used to investigate the performance of the TRMM Microwave Imager (TMI) land algorithm. In particular, data from a dense network of rain gauges being operated over the Korean Peninsula were utilized. To retrieve information related to the rainfall rate over land, the TRMM land algorithm relies mainly on brightness temperature $T_B$ depression at vertically polarized 85(V) GHz because of scattering by ice particles. It refers to the relationships between 85(V)-GHz $T_B$s and rain rates in its predefined database. By comparing the TMI rain rates with the surface rain gauge and TRMM radar measurements, it was found that there are a variety of relationships between 85(V)-GHz $T_B$s and rainfall rates resulting from the various types of precipitating clouds. The TMI land algorithm, therefore, could not resolve some raining clouds such as warm clouds as well as cold clouds having small amounts of ice particles above the rain layer. The rainfall amounts for those missed rain events are significant. As a result, rain rates produced by the land algorithm show systematic biases, which are a function of raining cloud types. Meanwhile, it is found that the 37-GHz TMI channels contain additional information on surface rain; the uncertainties in retrieving rain rates from $T_B$s at TMI frequencies can be reduced up to 11% if all polarized 37- and 85-GHz $T_B$s are used as predictors.

1. Introduction

The Tropical Rainfall Measuring Mission (TRMM) is one of the most successful weather satellite missions to use radiometric measurements at microwave frequencies for rain estimation from space (Simpson et al. 1988; Kummerow et al. 1998). The TRMM facility algorithm inverts brightness temperatures $T_B$s at TRMM Microwave Imager (TMI) frequencies into rain rates (RRs) based on the Bayesian theorem using a predefined database. The database has linkages between the TMI $T_B$s and cloud properties (Olson et al. 1999; Kummerow et al. 2000, 2001). Unlike the ocean algorithm that makes full use of emission and scattering signatures from observations at multiple frequencies, the land rain algorithm mainly relies on the scattering signature at 85 GHz by ice particles (Spencer et al. 1989; McCollum and Ferraro 2003; Kummerow and Ferraro 2006). Because of the complexity of land surface emissivity and the less direct relationship between ice scattering and surface rain rate, the quality of satellite rain retrievals over land is not as good as over the ocean (Lin and Hou 2008). To develop a better land rain retrieval algorithm, this study intends...
to gain a greater understanding of the brightness temperature response to rain rate over land for different cloud types.

To understand the response of brightness temperature to rain rate, we have collocated data from TMI and TRMM precipitation radar (PR) with data from a dense rain gauge network over the Korean Peninsula. Data from the dense rain gauges are particularly beneficial to this study, because they are direct measurements of surface rain, in contrast to the PR rain rate that is inverted from radar reflectivity at the lowest clutter-free (not influenced by ground clutter) range bin at each angle bin. In the data analysis, we first investigate how the 85-GHz brightness temperature responds to rain rate of various rain types. The result from this analysis will suggest which type of clouds the current TRMM facility algorithm works well for and which type of clouds it does not. Then, we explore whether and how brightness temperature measurements at other TMI channels can provide additional rainfall information.

2. Data

For this study, the TMI $T_{B}$s are collocated with rain rate retrievals from TMI and PR and rain rate measurements from the gauge network over the Korean Peninsula. The TMI measures radiation at 10.65, 19.35, 37.0, and 85.5 GHz with both horizontal and vertical polarizations and at 21.3 GHz with vertical polarization. It covers the tropics and subtropics (35°S–35°N). The TRMM facility land algorithm primarily uses only 85-GHz $T_{B}$s for rain rate retrievals, whereas 21-GHz $T_{B}$s are included in the algorithm to screen nonraining pixels. Those pixels whose vertically polarized $T_{B}$ difference between 21 and 85 GHz is less than 8 K and whose horizontally polarized 85-GHz $T_{B}$ is greater than 270 K are considered as nonraining pixels (McCollum and Ferraro 2003; Kummerow and Ferraro 2006). The PR is a scanning radar operating at 13.8 GHz with a sensitivity of about 17 dBZ, corresponding to about 0.7 mm h$^{-1}$ in rain rate (Iguchi and Meneghini 1994). For the comparison with the TMI rain estimates, the standard version 6 products, 2A25 and 2A23, were obtained from the National Aeronautics and Space Administration (NASA) Goddard Earth Sciences Data and Information Services Center. The PR pixels have a horizontal resolution of 5 km at nadir and a vertical resolution of 250 m from the earth surface to 20 km altitude. The vertical profiles of rain rate are calculated from radar reflectivity $Z$ profiles using a $Z$–$R$ relationship (Iguchi and Meneghini 1994; Iguchi et al. 2000). For this study, 2A25 near-surface rain rates are used in a comparison with the TMI rain rates, and the vertical profiles of attenuation-corrected radar reflectivity factor and rain types are used to analyze vertical structures of precipitation-sized hydrometeors.

The Korea Meteorological Administration runs approximately 500 automatic weather systems (AWSs) over the Korean Peninsula. Their mean distance between two nearest stations is about 9 km, constituting a dense surface gauge network (Fig. 1). These tipping-bucket rain gauges record rain accumulation every minute in a resolution of 0.5 mm. The rain accumulation is then converted into rain intensity using a spline-matching method. In performing the collocation of these data, the relations between TMI $T_{B}$ and rain gauge data can be quite different, depending on the searching radius within which data from all rain gauges are averaged. Seo (2009) calculated the correlation coefficients between TMI-retrieved RRs (TMI-RRs) and AWS-retrieved RRs (AWS-RRs) for several combinations of temporal windows and spatial ranges. The result shows that, for a given spatial search radius, the correlation coefficient increases with the time period over which the AWS RRs are averaged. In general, a larger spatial search radius yields a better correlation coefficient. Over ocean, the nominal scale of the TMI footprint of about 12.5 km $\times$ 12.5 km has been used by Olson et al. (2006) and Wolff and Fisher (2008). The nominal size might be reasonable for ocean, because TMI $T_{B}$s from various footprint sizes in the range of 5.5–50 km are involved in the ocean retrieval algorithm. However, because the relation between 85-GHz $T_{B}$ and AWS rain rate is investigated in this study, the nominal scale over land should be different from that over ocean. The horizontal scale of the 85-GHz footprint and PR resolution is about 5–5.5 km. The nominal scale of the TMI footprint becomes similar to the footprint size of 85 GHz (e.g., Seto et al. 2009). Considering the footprint size of 85 GHz, 3-km and 8-min search radii seem to be reasonable over
land for the collocation between TMI pixels and rain gauges. Thus, if the center of a PR pixel is located within 2 km from the center of an 85-GHz TMI pixel, the collocations between TMI and PR pixels were made. Then, data from all rain gauges located within a radius of 3 km and a time difference of 8 min were averaged to match the TMI–PR pixel. In the following analysis, we use data from 5 summers (June–August 2002–06) when gauge measurements are greater than 0 mm h\(^{-1}\).

3. The relation between 85-GHz \(T_B\)s and surface RRs

The TRMM TMI facility land rain algorithm relates RRs to the 85-GHz \(T_B\). Hence, let us first examine how 85-GHz \(T_B\)s are compared to the rain rates measured by three different instruments. The relationships between vertically polarized 85-GHz \(T_B\) (\(T_{B85v}\)) and TMI-RRs were plotted in Fig. 2a. Because the rain criterion based on horizontally polarized 85-GHz \(T_B\) (\(T_{B85h}\), i.e., \(T_{B85h} < 270\) K) for rain plays a key role in the land algorithm, most pixels with \(T_{B85v} > 270\) K were assigned a zero rain rate. The TMI-RRs are distributed in a narrow region in the figure and can be expressed by a simple linear function of \(T_{B85v}\) [i.e., \(T_{B85v} = f(RR)\)], which is the solid line in Fig. 2a. This simple function is the \(T_{B85v}\)–RR relation as presented by the facility algorithm. The PR-measured RRs (PR-RRs) and AWS-RRs are plotted in Fig. 2b against all collocated \(T_{B85v}\) pixels, along with the relation represented by \(T_{B85v} = f(RR)\). Unlike the TMI-RRs, the PR-RRs are not well correlated with \(T_{B85v}\). Many high rain rates correspond to relatively warm \(T_{B85v}\)s, and significantly high rain rates are found even for \(T_{B85v}\)s greater than 270 K (Seo 2009). In general, the AWS-RR or PR-RR versus \(T_{B85v}\) relation does not follow the trend as indicated by \(T_{B85v} = f(RR)\), in which most linkages between 85-GHz \(T_B\)s and rain rates in the facility algorithm database are confined.

To better understand the responses of \(T_{B85v}\) to different clouds, all data are divided into four categories based on the relationships between \(T_{B85v}\)s and AWS-RRs as follows:

\[
\text{category} = \begin{cases} 
1 & f(RR) - 20 < T_{B85v} < f(RR) + 20 \quad \text{and} \quad T_{B85v} < 270 \\
2 & T_{B85v} < f(RR) - 20 \quad \text{and} \quad T_{B85v} < 270 \\
3 & T_{B85v} > f(RR) + 20 \quad \text{and} \quad T_{B85v} < 270 \\
4 & T_{B85v} > 270,
\end{cases}
\]

where \(T_{B85v} = f(RR)\) is the solid line in Fig. 2. The two parallel dotted lines are the displacement of ±20 K from \(T_B = f(RR)\), and the horizontal line denotes \(T_{B85v} = 270\) K. Category 1 occupies 42.9% of rainy pixel occurrence and
28.5% of the rain amount on the basis of the ground AWS measurements (Table 1). By design, the TMI facility land algorithm performed well in category 1. Category 2, in which cold $T_{BSSV}$ correspond to low RRs, contains a small portion of rain pixels (1.7% in pixel fraction and 3.2% in rain amount). In category 3, the AWS measurements show 13.5% in pixel occurrence and 48.2% in rain amount. Clouds in category 3 produce a large amount of rain and have relatively warm $T_{BSSV}$. Pixels in category 4 have $T_{BSSV}$ warmer than 270 K but have measurable rain. There is a large portion of pixels in this category (40.4% in occurrence) that produces a significant percentage (21.6%) in respect to rain amount. Hence, it is important for land algorithms to capture the rainfall events in this category showing $T_{BSSV} > 270$ K. Furthermore, the role of rain types in the relations between 85-GHz $T_B$ and RRs was examined using PR 2A23 products (Fig. 2b). Even though convective and stratiform rain pixels are mixed considerably in all the categories in the domain of 85-GHz $T_B$ and rain rate, the linear regression line for all convective rain pixels is somewhat different from that for all stratiform rain pixels. Those regression lines exhibit quite differently from the relations representing category 1, in which most linkages between 85-GHz $T_B$ and rain rates in the land algorithm database are confined. Therefore, it seems to be important to expand the predefined database in terms of rain types as well as those various relations.

In the search for explanations to the above relationships between $T_{BSSV}$ and rain rate, the characteristics of vertical cloud structures were examined using PR reflectivity. In Fig. 3, the contoured frequency by altitude diagrams (CFADs; Yuter and Houze 1995) of the radar reflectivity profiles is shown for each category as well as all pixels. For all raining events, the CFADs were widely spread from low to high radar reflectivity, because various types of raining clouds are included (Fig. 3a). The most frequent radar reflectivity is found around 25–30 dBZ below 5 km and then decreases rapidly with increasing height above 5 km. Because about 43% of all raining clouds belong to category 1, the CFADs for category 1 are very similar to those of the previous CFADs for all raining events, although the spread is somewhat narrower. In particular, those clouds in category 1 have rain amounts proportional to ice amounts compared to the other categories. Therefore, they exhibit well balanced amounts of rain below freezing level around 5 km and ice above, compared to the other categories. According to 2A23 rain types, most of those clouds are stratiform rain (Fig. 2b). In fact, the predefined database that the facility land algorithm refers to tends to represent the relations between $T_{BSSV}$ and rain rates in category 1 (Fig. 2a). As a result, the facility land algorithm works quite well in this category. Unlike category 1, category 2 exhibits clouds that are distributed in a narrow range of radar reflectivity centered at $\sim 30$ dBZ below 5 km and 20 to $\sim 25$ dBZ above 5 km with a strong presence up to about 10 km. Those clouds are tall with thick ice layers above freezing level. Surprisingly, most rain events in category 2 exhibit stratiform rain (Fig. 2b). The sharp decrease of radar reflectivity around 5 km in the CFAD structure supports that those events are stratiform rain clouds having bright band near freezing level (Fig. 3c). On the other hand, some rain events are convective rain pixels, which are probably developing convective clouds having abundant precipitation-sized ices but a little amount of rain, which effectively scatter upwelling radiance from underlying rain clouds. Accordingly, they are capable of producing a significant depression in $T_B$. Hence, for a given rain rate, its $T_{BSSV}$ tends to be located below the line of $T_B = f(\text{RR}) - 20$. For category 3, the CFADs demonstrate characteristics of high reflectivity in the rain layer and rapid decrease in radar reflectivity above the rain layer compared to the other categories. This bottom-heavy CFADs pattern suggests that, for a given ice water amount above, there is a large amount of rain below compared to those clouds in categories 1 and 2. Many rain events in category 3 are convective rain (Fig. 2b). Those convective clouds as well as stratiform clouds in the category tend to have relatively small amount of precipitation-sized ices compared with rain amount. Consequently, the $T_B$ tends to be warmer than those in categories 1 and 2, given the same rain rate. The facility land algorithm underestimates rain rate because of the lack of ice scatter signature for clouds in this category. The CFADs in category 4 clearly display characteristics of warm rain clouds or weak stratiform rain clouds, resulting in warm $T_B$ ($\sim 270$ K). In addition, many rain events are classified as neither convective nor stratiform rain (Fig. 2b). However, those clouds produce a fairly large amount of rain. Therefore, the current facility land algorithm that linearly relates 85-GHz $T_B$ to rain rates has difficulties of estimating rainfall events in categories other than category 1. These classifications indicate that the predefined database needs to accommodate the relationships between $T_{BSSV}$ and rain rate for various rain types. To study the multilayered relations of hydrometeors, empirical orthogonal function (EOF) analysis is

<table>
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<tr>
<th>Table 1. Statistics of rain pixel and amount fractions based on the AWS-RRs in each category.</th>
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<tr>
<td>Simulation</td>
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<tr>
<td>Pixel fraction</td>
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<tr>
<td>Rain amount fraction</td>
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performed for vertical profiles of radar reflectivity. Radar reflectivities in the vertical do not vary independently with each other, because the vertical distribution of hydrometeors is controlled by cloud microphysical and dynamical processes that have a close linkage between atmospheric layers. Thus, EOFs provide multilayered relations. Let $Z_i$ represent a vector of the anomaly of the vertical reflectivity profiles for the $i$th data point. These anomalies can be expressed with respect to EOFs $e_j$ as $Z_i = \sum_j a_{ij} e_j$, where $a_{ij}$ is the amplitude for the $j$th EOF at point $i$ and $N$ is the number of EOFs. The eigenvalues from the EOF analysis quantify the amount of the total variation explained by the corresponding EOF. The first and second eigenvalues are shown in Fig. 4. They imply that the first and second leading EOFs can explain about 87% and 11% of the total variance of the collocated PR profiles, respectively. In other words, about 98% of total variance in the multivariate radar reflectivity profiles can be explained by two major EOFs (Fig. 4). The structure of the EOFs is sometimes closely related to physical processes within the clouds (e.g., Biggerstaff et al. 2006; Seo et al. 2007). The first EOF structure represents large variability concentrated in rain layer, whereas the second EOF structure denotes possibly cold (or tall) clouds having rain layers below coupled with ice layers above. Although the first EOFs have similar vertical characteristics, there are some differences among their structures. Among the EOF structures, the first EOF of category 4 displays a large variability confined to a very low layer, which is associated with very shallow clouds shown in Fig. 3e. The second EOFs have more complex variability with perturbations of the opposite sign at low levels and upper levels, implying a tendency of the increase (decrease) of liquid hydrometeors jointly with the decrease (increase) of ice hydrometeors aloft. The second EOFs of categories 1 and 2 are
attributed to variability from deeper clouds compared to the other categories. Note that most of the rain events in those categories are stratiform rain (Fig. 2b). Category 3 shows the largest eigenvalue in the first EOFs, indicating that 88% of the total variability in the radar profiles is caused by raindrops below freezing level. On the other hand, category 2 has the largest eigenvalue among all the second EOFs. This implies that category 2 is more closely related to variability in deep clouds, which are the coupled rain and ice layers. Thus, the EOF structures of PR observations can give us a valuable direction about how the simulated database needs to be built up so that the general characteristics of vertical distribution of hydrometeors in the database are consistent to those of observed radar reflectivity profiles. It should be noted that, in the above discussions using CFADS and EOF analysis, we have conveniently assumed that hydrometeors above freezing level are mostly ice particles. Although this assumption may hold true for stratiform clouds, for convective clouds a substantial portion of hydrometeors may remain to be supercooled liquid drops above freezing level. In such a case, a strong radar return is not necessarily an indication of large amount of precipitating ice. This uncertainty is a limitation of the interpretation given in this section.

4. The response of TMI $T_{B8}$ to surface RRs

In Table 2, the correlation coefficients between AWS-RRs and $T_{B8}$ of all TMI channels are listed, grouped by rain categories. For data of all categories, the 85- and 37-GHz $T_{B8}$s have correlations of about $-0.45$ to about $-0.48$ and about $-0.44$ to about $-0.49$, respectively, whereas 19- and 10-GHz $T_{B8}$s have very small correlations around 0.1; that is, the correlation decreases substantially as the frequency below 37-GHz decreases. In general, it is larger for vertically polarized channels than for horizontally polarized ones. This infers that 37- and 85-GHz can be of use to rain retrievals. The relationships between vertically polarized 37-GHz $T_{B8}$ ($T_{B37V}$) and rain rates of AWS and PR were plotted in Fig. 5. Although the dynamic range of 37-GHz $T_{B8}$ for rain events is smaller than that of 85-GHz $T_{B8}$, the relationship for 37 GHz is very similar to that for 85 GHz and, furthermore, the distribution in the region corresponding to category 2 is less scattered. Because ice scattering at 37 GHz tends to be sensitive to larger precipitation-sized ice particles than that at 85 GHz, those stratiform pixels with low-density snowflakes at upper layers seem to disappear in that region (Fig. 5). The feature is supported by the finding of Seto et al. (2009) that the rain

<table>
<thead>
<tr>
<th>Category</th>
<th>85V</th>
<th>85H</th>
<th>37V</th>
<th>37H</th>
<th>21V</th>
<th>19V</th>
<th>19H</th>
<th>10V</th>
</tr>
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<tbody>
<tr>
<td>Category 1</td>
<td>$0.75$</td>
<td>$0.71$</td>
<td>$0.70$</td>
<td>$0.65$</td>
<td>$0.40$</td>
<td>$0.18$</td>
<td>$0.00$</td>
<td>$0.03$</td>
</tr>
<tr>
<td>Category 2</td>
<td>$0.80$</td>
<td>$0.77$</td>
<td>$0.71$</td>
<td>$0.68$</td>
<td>$0.36$</td>
<td>$0.15$</td>
<td>$0.06$</td>
<td>$0.15$</td>
</tr>
<tr>
<td>Category 3</td>
<td>$0.73$</td>
<td>$0.70$</td>
<td>$0.70$</td>
<td>$0.68$</td>
<td>$0.49$</td>
<td>$0.28$</td>
<td>$0.17$</td>
<td>$0.16$</td>
</tr>
<tr>
<td>Category 4</td>
<td>$0.24$</td>
<td>$0.24$</td>
<td>$0.02$</td>
<td>$0.12$</td>
<td>$0.10$</td>
<td>$0.19$</td>
<td>$0.22$</td>
<td>$0.13$</td>
</tr>
<tr>
<td>All categories</td>
<td>$0.48$</td>
<td>$0.45$</td>
<td>$0.49$</td>
<td>$0.44$</td>
<td>$0.33$</td>
<td>$0.12$</td>
<td>$0.00$</td>
<td>$0.03$</td>
</tr>
</tbody>
</table>
overestimation in the Global Satellite Mapping of Precipitation (GSMaP) when storm height is higher than 10 km is mitigated by using 37-GHz observations as a scattering signal; that is, retrieval algorithms using scattering signature at 85 GHz over land might lead to overestimation of rain rate for stratiform rain clouds that contain a large amount of precipitating ice particles. Hence, for those clouds, 37-GHz observations could be another supplementary predictor for rain rate in addition to 85-GHz observations. The $T_B$s at these two frequencies show high correlations (0.65 in absolute values) in categories 1–3, whereas their correlations in category 4 are less than 0.25 (in absolute value). As a result, data in category 4 reduces the overall correlations for the whole dataset to 0.46 for 37- and 85-GHz $T_B$s, because this category occupies a considerable fraction of 40% in occurrences and a fraction of 22% in rain amount. The high correlation between rain rates and 37-GHz $T_B$s is somewhat surprising. So far, it is commonly believed that 85-GHz $T_B$s have predominant rainfall signature over land because of its high sensitivity to ice scattering, whereas lower-frequency channels are generally rain blinded over land. In fact, the TMI facility land rain algorithm, as well as many other microwave rain land algorithms, has been designed to let rain rate approximately proportional to the depression (relative to rain free) of 85-GHz brightness temperature. From the results of the above correlations analysis based on ground rain measurements, it is clear that 37-GHz brightness temperatures contain rainfall information at a similar magnitude to that of 85 GHz. Thus, further investigation of its usage in the future will certainly be beneficial for improving microwave rain retrieval over land.

5. Conclusions

In satellite microwave remote sensing of rainfall, the performance of overland algorithms are less accurate than that of over-ocean ones. The primary reason is that overland algorithms are based on the correlative relation of the amount of ice particles aloft to the intensity of surface rain. This relation is generally not as close as that between columnar liquid water path and surface rain intensity, which over-ocean algorithms are primarily based on.

In this study, using collocated data from a densely populated surface rain gauge network, TRMM PR and TMI, we investigated how the TMI high-frequency (85 GHz) $T_B$s are related to surface rain rates. We divided the data into four categories based on how the TMI facility land algorithm performed: 1) reasonably well, 2) serious underestimation, 3) serious overestimation, and 4) unable to detect. By analyzing the vertical structures, it is found that clouds in category 1 have a well-balanced vertical distribution of ice aloft and liquid below; those in category 2 have anomalous more ice aloft, whereas those in category 4 have anomalous more liquid below. The clouds associated with category 4 (that TMI algorithm cannot detect) are likely to be warm clouds or weak stratiform clouds. It is necessary to point out that clouds in category 1, for which the facility algorithm does well, only produce about one-third of total rain for the studied cases (five summers over the Korean Peninsula).

Another finding of the study is that, in addition to 85 GHz, the $T_B$ at 37 GHz contains similar amount of information on surface rain over land. This is somewhat different from our current understanding that only 85-GHz $T_B$s in TMI channels have strong signature of overland surface rain. Further physical understanding and subsequent use of the 37-GHz signature in retrieval algorithms are certainly needed in the future.

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