Application of lightning to passive microwave convective and stratiform partitioning in passive microwave rainfall retrieval algorithm over land from TRMM

Nai-Yu Wang,1 Kaushik Gopalan,1 and Rachel I. Albrecht2

Received 21 March 2012; revised 14 August 2012; accepted 6 October 2012; published 7 December 2012.

[1] This study analyzes relationships between lightning flash rate, radar reflectivity factor (reflectivity), and passive microwave brightness temperature (Tb) for convective and stratiform precipitation over land using multiyear data from the Tropical Rainfall Measuring Mission (TRMM) satellite. A new convective and stratiform index (CSI (an estimate of convective areal fraction)) for the TRMM Microwave Imager (TMI) is developed from the analysis. Four years of TRMM TMI, Lightning Imaging Sensor (LIS), and Precipitation Radar (PR) data (2002–2005) are colocated and remapped to 0.1 and 0.05 degree grids for analysis. The scientific objective of this study is to understand the relationship between lightning and active and passive microwave precipitation observations and explore ways of using lightning information to enhance the discrimination between convective and stratiform precipitation in TMI rain rate retrieval algorithm. PR provides the reference convective and stratiform classification and is coincident with LIS which reports lightning parameters such as the occurrence (yes or no) and flash rates. Analysis of ~14 million coincident precipitating TRMM measurements over land (i.e., excluding oceans and coasts) reveals that 6% of rain data have lightning flash rates greater than zero. For all lightning data, 60% have 0–1 fl min⁻¹, 28% have 1–2 fl min⁻¹, and 12% have flash rates greater than 2 fl min⁻¹. Overall, 86.5% (13.5%) of lightning occurred in convective (stratiform) precipitation. In other words, stratiform rainfall is predominant when LIS detects no lightning, and the convective rain probability increases with increasing lightning frequency. For example, 34% of rainfall is convective for low flash rates (0–1 fl/min), whereas the convective probability increases to 99.7% for high flash rates (≥2 fl/min). This study develops a simple method that incorporates lightning into the CSI to test if lightning can help passive microwave (PM) delineate convective and stratiform precipitation. LIS lightning occurrence and flash rates (i.e., no flash, 0–1 fl/min, 1–2 fl/min, and >2 fl/min) are used to preclassify TMI Tbs into four groups of increasing convective probability. Multivariable linear regression is then applied to each group to derive the CSI. Results reveal that lightning information primarily improves the identification of highly convective rainfall by correctly shifting microwave observations previously identified as moderate to highly convective. Alternatively, the absence of lightning also helps PM to identify likely stratiform. Overall, including lightning information results in a decrease of bias error of 6% and a small increase in RMS error of 4.5% on the entire range of rainfall rates.


1. Introduction

[2] The next generation geostationary weather satellite (Geostationary Operational Environmental Satellite – R series, GOES-R) is an important improvement over current GOES technology and is scheduled to launch in 2015. GOES-R will host two main weather instruments: the Advanced Baseline Imager (ABI) and the Geostationary Lightning Mapper (GLM). The baseline GOES-R ABI rainfall rate Quantitative Precipitation Estimation (QPE) algorithm [Kuligowski, 2002] requires
microwave-based rain rates as a calibration target. One of the main difficulties in overland passive microwave (PM) rainfall retrievals is delineating convective and stratiform precipitation. Fortunately, passive microwave (PM) precipitation signals are sensitive to the presence of ice, which is also key for lightning generation. Since lightning activity provides a good indicator of deep convection, collocated total lightning (cloud-to-ground and intracloud) observations may help improve the microwave definition of convective and stratiform precipitation, and in turn improve the rainfall retrievals necessary for calibration of the GOES-R QPE algorithm. The upcoming Global Precipitation Measurement Mission (GPM, scheduled to launch in 2014), also will benefit from the analysis, providing a calibration source for the GOES-R QPE algorithm.

Various PM precipitation algorithms employ a convective and stratiform partitioning scheme to determine a convective fraction for each pixel. Methods for calculating the convective fraction typically use the 37 and 85 GHz liquid water emission and ice scattering signal from a single pixel, as well as spatial variability of rainfall such as the minimum 85 GHz Tb, as well as the gradient and standard deviation of 85 GHz Tb from adjacent pixels [Anagnostou and Kummerow, 1997; Grecu and Anagnostou, 2001; Kummerow et al., 2001; Olson et al., 2001; McCollum and Ferraro, 2003; Dinku and Anagnostou, 2006; Gopalan et al., 2010]. Our study investigates the use of lightning information, in conjunction with PM, to maximize the correlation between convective precipitation and PM measurements. The main scientific objective of this study is to use lightning information to improve PM’s ability to discriminate between convective and stratiform precipitation.

Higher-frequency passive microwave Tbs upwelling from clouds and precipitation are closely related to the ice hydrometeors in the atmosphere. At frequencies ≥85 GHz, ice layers of any significant optical thickness are effective insulators that they greatly backscatter passive microwave radiation emanating from below due to the relatively warmer liquid cloud and surface emission and backscatter sources. Thus, the resultant remotely sensed ice cloud signature is typically a buildup of more and more suppressed (colder) brightness temperatures as ice optical thicknesses increase toward the centers of convection as Tb depressions. The optical depths of the ice layers are a function of the bulk ice particle densities, size distributions, number densities, and geometric depths of the layers [Smith and Mognai, 1988, 1989; Mognai et al., 1990, 1993; Vivekanandan et al., 1990, 1991; Smith et al., 1992]. Surface emission is mostly a function of the near surface wetness (i.e., soil moisture, canopy water sources, etc.) while surface scattering properties are a function of microwave-scale facet geometry and dielectric properties. Whereas, cloud water can produce a warming signal that can offset the cooling signal produced by ice scattering [Adler et al., 1991; Wang et al., 2009], numerous observational and modeling studies have consistently shown that the strongest ice backscattering signals, and thus the strongest 85 GHz suppressions, are associated with deep ice layers that contain many large graupel/hail-size ice particles [Wilheit et al., 1982; Wu and Weinman, 1984; Hakkarinen and Adler, 1988; Mohr and Zipser, 1996; Schols et al., 1999; Nesbitt et al., 2000; Petersen et al., 2005].

Previous studies have shown that the ice-ice collision charging mechanism (i.e., the noninductive charging mechanism) is responsible for the robust electrical charge separation in thunderstorms [Takahashi, 1978; Jayaratne et al., 1983; Saunders et al., 1991; Williams et al., 1991; Rutledge et al., 1992; Zipser and Lutz, 1994; Petersen and Rutledge, 1998, 2001; Blyth et al., 2001; Petersen et al., 2005; Takahashi and Miyawaki, 2002; Wiens et al., 2005; Saunders et al., 2006; Latham et al., 2007; Deierling et al., 2008]. The noninductive charging mechanism describes the exchange of electric charges during collisions between precipitation-sized ice particles (i.e., hail and graupel) and smaller ice particles in the presence of supercooled liquid water in the convective updraft of thunderstorms. There is a strong correlation between the amount of precipitation-sized ice mass in deep convection and lightning production [Blyth et al., 2001; Petersen and Rutledge, 2001; Petersen et al., 2005; Latham et al., 2007; Deierling et al., 2008]. Blyth et al. [2001], Petersen and Rutledge [2001] and Petersen et al. [2005] used satellite observations and theory to demonstrate a linearly non-linear relationship between lightning flash rate and precipitation ice water path (IWP). Furthermore, while relationships between convective rainfall and lightning vary geographically, the IWP-lightning relationship is relatively invariant between oceanic, coastal, and continental regimes [Petersen et al., 2005].

Several studies have examined the use of lightning to improve satellite rainfall estimates [Goodman et al., 1988a; Grecu et al., 2000; Morales and Anagnostou, 2003; Chronis et al., 2004]. These studies improved rain rate estimates by combining infrared (IR) channels and cloud-to-ground lightning to develop lightning-IR Tb algorithms. For example, Grecu et al. [2000] found a reduction of about 15% in the root-mean-square (RMS) error of the rain volume estimates for convective areas with lightning; Morales and Anagnostou [2003] found a 31% bias reduction in the convective rain area; and Chronis et al. [2004] showed significantly lower RMS error differences (25%–40%) compared to IR-only retrievals. These improvements result from the fact that IR measurements have a weak physical relationship to convective rain processes, where lightning information is most beneficial.

This study further addresses the hypothesis that lightning can be used to help PM better delineate convective and stratiform precipitation. Four years (2002–2005) of TRMM TMI, LIS and PR data are colocated and used to derive a physically reasoned and statistically formulated convective and stratiform partitioning scheme. The two main goals are to better understand the relationship between lightning and microwave convective properties, and explore ways to maximize the correlation between microwave Tb and lightning observations of convective precipitation over land.

Section 2 first summarizes the database and background used for the estimation of precipitation type and rate from TMI. Section 3 then characterizes lightning, radar reflectivity, and microwave ice scattering signals over land, providing foundation and motivation for the application of lightning to passive microwave convective and stratiform precipitation partitioning. Section 4 next evaluates the benefits of using lightning information to improve precipitation type classification in the
rainfall retrieval algorithm, while section 5 presents conclusions and recommendations for future research.

2. Data and Background

2.1. Data

[9] This study uses data from the Tropical Rainfall Measuring Mission (TRMM) satellite. TRMM was launched in late November 1997 at an altitude of 350 km and an 35° inclination, and was boosted to 402.5 km in August 2001 to prolong the mission life. TRMM incorporates, among others, three state-of-the-art instruments that work separately, but in conjunction with each other to detect and measure precipitation and lightning flash rates. These instruments are the Precipitation Radar (PR), the TRMM Microwave Imager (TMI) and the Lightning Imaging Sensor (LIS).

[10] PR was the first earth satellite-based precipitation radar designed to provide detailed three dimensional rain structure information. PR operates at 13.8 GHz with a 247 km swath and approximately 5 km horizontal and 250 m vertical resolutions [Kummerow et al., 1998, 2000]. This detailed information on the vertical rain profile provides accurate information on rain type, rain layer depth and top height, and melting layer (bright band height). PR rain type classification algorithm (2A23) uses two independent methods [Awaka et al., 2007], a vertical profile method [Awaka et al., 1997], and a horizontal pattern method [Steiner et al., 1995]. The algorithm combines these two methods to classify PR pixels as stratiform, convective, or other.

[11] TMI is a multichannel passive microwave radiometer that measures atmospheric upwelling Tbs at five frequencies: 10.7, 19.4, 21.3, 37 and 85.5 GHz. Each frequency has two channels, one vertically polarized and one horizontally polarized, except for 21.3 GHz which has only one vertically polarized channel [Kummerow et al., 1998, 2000]. The TMI footprint size ranges from ~8 x 5 km for the 85.5 GHz channels up to ~70 x 40 km for the 10.7 GHz channels. The spatial sampling frequency is ~5 km for the 85.5 GHz channels and ~10 km for the lower-frequency channels, while the full swath width is around 880 km. The lower-frequency (10.7 GHz to 37 GHz) data are linearly interpolated in the along-scene direction to match the sampling of the 85.5 GHz data. Since this study relies on collocated measurements from TMI, PR and LIS, only the inner one third of the TMI footprint is used.

[12] LIS mainly consists of a staring charge coupled device (CCD) array that detects total lightning (cloud-to-ground and cloud-to-cloud) events at the neutral oxygen line in the near infrared (777.4 nm), which is one of the strongest optical emission lines in the lightning spectrum [Christian and Goodman, 1987; Goodman et al., 1988b]. The LIS field of view is 668 km, with 4.3 km spatial and 2 ms temporal resolutions at nadir. A lightning event is captured within a single pixel of the CCD array exceeding the background threshold during a single 2 ms frame. As lightning discharges illuminate multiple pixels within multiple frames, the events are grouped in space and time to form a “flash.” The flash location is determined by a weighted mean of the radiances of the events. Therefore, a LIS lightning flash represents one or more pulses that occur in the same storm cell within a specified time and distance [Christian et al., 2000]. The LIS flash detection efficiency is 90% and nearly uniform within its field of view (FOV), and LIS detects both intracloud and cloud-to-ground discharges (total lightning) throughout day and night [Christian et al., 2000; Boccioppio et al., 2002]. Since this study relies on collocated measurements from TMI, PR and LIS, only the inner LIS FOV (which overlaps with the PR swath) is used.

[13] To illustrate LIS (i.e., events to flashes), PR, and TMI observations, Figure 1 shows the vertically polarized TMI 85.5 GHz Tb (Tb85V) (Figure 1a), the PR near surface reflectivity (Figure 1b), as well as LIS event (Figure 1c) and flash (Figure 1d) rates observed by TRMM on 10 October 2004 over Brazil. When a lightning flash occurs several pixels of LIS CCD array are illuminated, each illuminated pixel of a single frame (2 ms) is a LIS lightning event. The frequency of events in Figure 1c is shown as events per minute in 0.1 degree boxes. It can be seen that lightning illuminated a large area of the precipitation system. In the regions centered at (1) (~27.2, ~50.2), (2) (~25.9, ~51.5) and (3) (~26.8, ~52.8) (in dark blue color in Figure 1c), the event rates are greater than 180 events per minute. As a lightning discharge resulted in several adjacent events, a flash is defined by a time and distance criteria to group the events. The frequency of flashes is then shown in Figure 1d in flashes per minute in 0.1 degree boxes. It is noticed that three regions with high event rates (>180 events per minute) show very different flash rates, i.e., (1) 0.65, (2) 2.0 and (3) 5.4 flashes per minute. The reason for this behavior is that the events in region 1 happened very close in time and hence belonged to a few number of flashes (each flash produced many events), while in the case of region 3 the events happened in a relatively longer period of time and hence were grouped to a greater number of flashes (each flash produced a few events). The pixel with the highest flash rate (6.3 flashes per minute – the yellow pixel at the location of (~26.3, ~53.4) in Figure 1d) has 51 events per minute, which is a result of a few events separated by a relatively long period of time, resulting in a few events assigned to several different flashes.

[14] This figure shows that the coldest Tbs (Tb85V < 170 K) are associated with frequent lightning events and flash rates (>100 events per minute, and >3.5 flashes per minute), indicating deep convection and well developed mixed and ice phases in the cloud. However, lightning activity also is found at relatively warm Tb85V (>210 K). When compared to the near surface PR reflectivity, it is found to be over 40 dBZ where Tb85V > 210 K and flash rate >1 fl min$^{-1}$, clearly indicating convective rain. This example illustrates these three observables (lightning flash rate, radar reflectivity, and passive microwave Tb85V) describe different but complimentary views of the microphysical composition of a precipitation system. Each provides independent information but must be consistent with the others. Together they paint a picture of the intensity (or lack of) and coverage of convection in a precipitation system. In sections 3 and 4 we will investigate the relationships between these three observables and convection and develop a method to use lightning information to delineate convective areas that are not as apparent in passive microwave observations.

2.2. Background

[15] The current overland TMI rainfall estimate algorithms (version 6 [McCollum and Ferraro, 2003] and version 7 [Gopalan et al., 2010]) were calibrated by applying PR 2A25
surface rain rates and 2A23 rain type to multichannel TMI Tb measurements. This study uses 4 years (2002–2005) of collocated Version 6 PR, TMI, and LIS measurements to derive a new convective stratiform index for TMI with additional lightning information from LIS. The PR and LIS data were matched to the TMI 85.5 GHz sampling resolution. Specifically, the measurements from all PR pixels nearest a TMI pixel were averaged to obtain the mean rainfall type and rate at that point. The PR pixel 2A23 rain type values (i.e., 1 for convective certain, and 0 for stratiform certain) then were averaged within the TMI 85 GHz footprint to obtain the convective fraction (i.e., continuous value, between 0 to 1). LIS view times and flash counts, gridded at 0.1° grid resolution, nearest the TMI pixel center then were used to compute flash rates (i.e., flashes per minute, fl min⁻¹) for each TMI pixel.

[16] TMI Tb and LIS flash rates also were matched to the PR resolution to investigate the relationship between the lightning frequency, radar reflectivity profile, Tb, and precipitation type, which will be discussed further in section 3. For the analysis, each PR profile is matched with its nearest TMI sample and LIS observation (gridded at 0.05° resolution). We stratified the data by lightning intensity and studied the differences in convective intensity (as measured by PR) between the lightning stratifications. The impact of incorporating lightning information in the passive microwave estimation of the convective fraction of precipitation is discussed in section 4.

Figure 1. (a) Vertically polarized TMI 85.5 GHz TB ($T_{b85V}$, K), (b) PR near surface reflectivity ($Z$, dBZ), (c) LIS event, and (d) flash rates (events per minute and flashes per minute in 0.1° × 0.1° grid resolution for Figures 1c and 1d, respectively) for a precipitating system observed by TRMM on 10 October 2004 over Brazil (TRMM orbit 39346). The solid black lines represent Brazil’s state political divisions, and the shaded gray image in Figures 1c and 1d are the view time (s) of LIS CCD. The area “illuminated” by the lightning discharges (all events) is represented by white pixels in Figure 1c. Yellow solid lines delineate PR, TMI and LIS coincident coverage, representing the data set (for each TRMM orbit) used in our study.
TMI surface rain rates (RR) primarily are estimated using the \(T_{BS5V}\) scattering signal. Since McCollum and Ferraro [2003], Wang et al. [2009], and Gopalan et al. [2010] provide detailed discussion of the TMI algorithm, only a brief outline is presented here. The algorithm estimates RR using empirically derived \(T_{BS5V} - RR\) relationships from TMI \(T_{BS5V}\) and PR surface rain rate. Multiple years of colocated TMI and PR data also were used to derive separate RR relationships for convective and stratiform rainfall. The RR estimates for convective and stratiform rainfall are combined for each pixel by estimating the convective P(C), and stratiform (1-P(C)) fractions:

\[
RR = RR_{conv} \cdot P(C) + RR_{strat} \cdot (1 - P(C)),
\]

where \(RR\) is the TMI rain rate estimate, \(RR_{conv}\) and \(RR_{strat}\) are the convective and stratiform rain rates for a given \(T_{BS5V}\), and \(P(C)\) is the TMI estimated convective fraction in the 85V FOV. \(P(C)\) also referred to as the convective stratiform index (CSI).

This study uses a similar approach to the current TRMM V7 TMI overland rain retrieval for estimating convective fraction, but also includes lightning. The convective fraction \(P(C)\) or CSI is calculated using the following linear regression of multichannel TMI Tbs and PR estimated convective and stratiform classification:

\[
P(C) = a_1 T_{BH01} + a_2 (T_{BS5V} + T_{BS37})/2 + a_3 NPOL
+ a_4 STDEV + a_5 MINIMA + k,
\]

where \(T_{BH01}\), \(T_{BS5V}\) and \(T_{BS37}\) are the vertically polarized 10, 37 and 85 GHz Tbs, NPOL is the normalized vertical and horizontal polarization differences at 85 GHz [Olson et al., 2001], \(STDEV\) is the \(T_{BS5V}\) standard deviation in a 40 x 40 km area, and \(MINIMA\) is the local \(T_{BS5V}\) minimum and spatial gradient of the four neighboring footprints [Prabhakara et al., 2000]. The variables \(a_1\) to \(a_5\) are the multiplicative coefficients of the multiple linear regression equation, and \(k\) is its regression constant. There are some differences in equation (2) from the ones used in the TMI V7 rain retrieval algorithm and from McCollum and Ferraro [2003]. We observed that the TMI TB85V and TB37V were highly correlated with each other (Correlation coefficient ~0.8) and had similar correlation with the convective fraction; that is, the information content about the convective fraction in both inputs is largely redundant. Therefore, instead of using TB85V and TB37V, we use the mean value of TB85V and TB37V as a single input in the regression. Additionally, McCollum and Ferraro [2003] used both the vertical – horizontal polarization difference at 85 GHz (POL) and the NPOL variable as regression inputs, whereas we have omitted the 85 GHz polarization input. We found that the POL and NPOL variables are highly correlated (correlation coefficient is >0.9); however the NPOL variable is significantly better correlated with the convective fraction. Therefore, we excluded the POL variable from the regression and verified that the exclusion has a negligible effect on the skill in estimating the convective fraction. Lightning information is incorporated by stratifying the data into four flash rate categories, which is equivalent to classifying the TMI Tbs into categories with increasing convective activity before estimating convective fraction P(C). The new P(C) relationships derived from the 4 years of TMI/PR/LIS data from January 2002 to December 2005 are further discussed in section 4.

3. Characteristics of Lightning Flash Rate, Passive Microwave Tbs, and Radar Reflectivity Over Land

Several studies have investigated relationships between radar, passive microwave, and lightning observations of precipitating ice particles and electrification [e.g., Toracinta et al., 2002; Petersen and Rutledge, 2001; Petersen et al., 2005; Cecil and Zipser, 2002; Deierling et al., 2008; Xu et al., 2010; Liu et al., 2011]. These investigations have documented empirical relationships between lightning intensity (e.g., flash rate) and convective parameters (such as updraft velocity, precipitation, ice water content). For example, Toracinta et al. [2002] used lightning frequency information to classify TRMM PR reflectivity profiles, Cecil and Zipser [2002] studied the radiometric and electrification properties of well-formed hurricane eye walls, and Liu et al. [2011] documented correlations between lightning flash rate and PM Tb. These previous studies all found that lightning formation is a strong indicator of convective precipitation and the presence of ice and mixed phases. Therefore, this section uses coincident lightning and microwave observations from TRMM to further document relationships between lightning activity and convective structure over land.

Based on over 14 million colocated precipitation data points over land (i.e., rain detected both by PR and TMI), 6% of rain data have lightning flash rates greater than zero. For all lightning data, 60% have 0–1 fl min\(^{-1}\), 28% have 1–2 fl min\(^{-1}\), and 12% have flash rates greater than 2 fl min\(^{-1}\). Overall, 86.5% (13.5%) of lightning occurred in convective (stratiform) precipitation. We next examine relationships between LIS flash rate, PR reflectivity, and TMI \(T_{BS5V}\). Figure 2 illustrates the relative frequency of occurrence for lightning flashes (Figure 2a) and the mean flash rate (Figure 2b) as a function of \(T_{BS5V}\) and the maximum PR reflectivity above the freezing level. For tropical continents, lightning occurrence and flash rate generally increase with decreasing \(T_{BS5V}\) and increasing radar reflectivity. The coldest \(T_{BS5V}\) correspond to areas with the greatest lightning activity (i.e., high likelihood of lightning occurrence and flash rates) and the greatest ice content, where ice scattering processes dominate. Areas with high flash rates also suggest a large concentration of cloud ice (i.e., low \(T_{BS5V}\)), principally in the form of precipitation as indicated by data. For data points with reflectivity less than 35 dBZ and \(T_{BS5V}\) warmer than 160 K, there is a low likelihood of lightning (<20%, Figure 2a) and average flash rates less than 1 fl min\(^{-1}\) (Figure 2b). The average flash rate is 1 fl min\(^{-1}\) for 40 dBZ and \(T_{BS5V}\) between 100 and 260 K (Figure 2b). For 40 dBZ radar reflectivity, lightning occurrence is 10% at 200 K increasing to 40% at 120 K. When radar reflectivity reaches 55 dBZ, 60–70% of the data contains lightning for a \(T_{BS5V}\) range from 100 to 280 K, and the average flash rates increase from 1 fl min\(^{-1}\) at the warm \(T_{BS5V}\) to 3 fl min\(^{-1}\) at the cold \(T_{BS5V}\). High flash rates (>2 fl min\(^{-1}\)) typically have maximum reflectivity greater than 40 dBZ and \(T_{BS5V}\) colder than 190 K (Figure 2b). Our results are in agreement with the findings of Toracinta et al. [2002], Xu et al. [2010] and Liu et al. [2011].
Figure 2b suggests that we can subset data containing lightning into 3 different lightning flash rate categories; data where LIS detects 0 to 1 fl min$^{-1}$ (Category 1, CAT1), 1 to 2 fl min$^{-1}$ (Category 2, CAT2), and greater than 2 fl min$^{-1}$ (Category 3, CAT3). Table 1 lists the definitions and descriptions of the CAT0 to CAT3 categories. Recall that 6% of pixels have lightning, so 94% have no lightning (Category 0, CAT0), 3.4% are CAT1, 1.6% are CAT2, and 0.6% are CAT3. The PR23 rain type algorithm classifies pixels as convective in 34% of CAT1 pixels, 47% of CAT2, and 99.7% of CAT3. Thus, CAT3 data are almost always convective, while CAT1 and CAT2 are most likely convective, or represent a transition area between convective and stratiform regions. CAT0 contains 6% of convective pixels, 61% of stratiform pixels, and 33% cannot be unambiguously determined by PR classification algorithm as either convective or stratiform. Hence, CAT0 pixels are essentially nonconvective.

To further illustrate the main characteristics of each lightning category, we next discuss relationships between LIS flash rates, PR reflectivity, and TMI 85 GHz Tbs (Figure 3). Convective pixels are divided into four flash rate (FR) categories (i.e., FR = 0, 0 < FR <= 1 fl min$^{-1}$, 1 < FR <= 2 fl min$^{-1}$ and FR > 2 fl min$^{-1}$), while stratiform pixels (where high flash rates are rare) are divided into 2 flash rate bins (i.e., FR = 0 and FR > 0). Figures 3a and 3b show the median and standard deviation of PR reflectivity profiles for each of these 6 categories. Stratiform pixels have smaller peak reflectivities, lower storm heights (i.e., weak updraft), and warmer $T_{B85V}$ than convective pixels. Stratiform profiles are similar regardless of lightning occurrence, differing by only a few dBZ (1–5 dBZ), and stratiform medium profiles are at least 7 dBZ lower than any of the median convective profiles in Figure 3a. On the other hand, the $T_{B85V}$ distributions between stratiform rain without lightning and with lightning are nicely stratified in Figure 3c. Stratiform rain with lightning peaks at 220 K, whereas stratiform rain without lightning peaks at much warmer 85 GHz brightness temperature of 260 K.

For convective pixels, the categories with more frequent lightning tend to have greater peak reflectivity (i.e., supercooled liquid water and large size ice particles, e.g., ice, hail and graupel, Figure 3a), cooler $T_{B85V}$ (i.e., large IWP, Figure 3c), and greater surface reflectivity (i.e., heavy surface precipitation, not shown here). Although these convective profiles show a broad range of $T_{B85V}$, the relative frequency of colder temperatures generally increases with increasing lightning rates (Figure 3c). The convective categories also tend to have deeper storm structures, with greater reflectivity values (>40 dBZ) extending to higher altitudes, indicating strong updrafts and active convection. For example, the median reflectivity profile of convective pixels with 0 < FR <= 1, shows that 40 dBZ reflectivity extend to 3.5 km,

<table>
<thead>
<tr>
<th>Table 1. Definitions and Descriptions of TRMM TMI-LIS Lightning Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
</tr>
<tr>
<td>Category 0 (CAT0)</td>
</tr>
<tr>
<td>Category 1 (CAT1)</td>
</tr>
<tr>
<td>Category 2 (CAT2)</td>
</tr>
<tr>
<td>Category 3 (CAT3)</td>
</tr>
</tbody>
</table>
above which they decrease gradually to 30 dBZ at ~7 km. Profiles of more electrically active convective pixels (i.e., FR > 2) exhibit reflectivity >30 dBZ up to 11 km, and reflectivity >44 dBZ at 3.5 km (i.e., lower levels). However, there is significant overlap between the PR reflectivity distributions of the different categories (Figure 3b). For convective pixels, the standard deviations of the PR reflectivity range from 6 dBZ to 7.5 dBZ at lower altitudes (up to 6 km) and decrease to 4.5 dBZ to 5.5 dBZ at the highest altitudes (Figure 3b). The standard deviations for stratiform pixels are 5.5 dBZ at the lower altitudes and decrease below 3.5 dBZ at the highest altitudes.

4. Lightning Application to CSI and Rain Rate Retrieval and Evaluation

4.1. Application

[24] Using the relationships between lightning flash rates and convective properties discussed in section 3, TMI Tbs are preclassified into four groups of increasing lightning probability. Four sets of coefficients for CSI using equation (2) from the four groups of TMI Tbs are listed in Table 2.

[25] For common Tbs, the CSI estimates reveal increasing convective fraction with increasing convective strength as indicated by greater lightning flash rates. For example, for the median TMI values ($Tb_{10V} = 275$ K, $0.5*(Tb_{37V} + Tb_{85V}) = 260$ K, NPOL = 0, STDEV = 10 K, MINIMA = 0), the convective fraction estimates are 0.05 (CAT0), 0.25 (CAT1), 0.41 (CAT2), and 0.97 (CAT3) versus 0.05 for TMI only. Thus, by using the different sets of coefficients for pixels with similar TMI observations, we are able to assign large convective probabilities for pixels with more lightning.

Table 3 shows the 5th percentile, the median, and the 95th percentile of the convective fraction for each of the four categories. TMI-only convective fraction estimates are generated using a single regression of TMI observations for all pixels (TMI algorithm). These estimates then are compared with estimates generated using different regressions for each category.

Figure 3. (a) Median reflectivity profiles for convective and stratiform rain types separated by lightning activity, (b) standard deviation of the median reflectivity profiles in Figure 3a, and (c) $Tb_{85V}$ histograms for each subset in Figure 3a, from January 2002 to December 2002.
lightning category (TMI-LIS algorithm). TMI-LIS estimates produce small convective fraction for CAT0 (i.e., no lightning), and 0, 0.09 and 0.47 for the 5th, median and 95th percentile, respectively), as well as higher convective fractions for greater lightning activity. Although a similar trend is observed in the TMI-only estimates, the increase in convective fraction estimates is not as substantial as the TMI-LIS estimates. The category with the most lightning (CAT3), consists almost exclusively of convective pixels, and the median convective fraction value (0.996) is consistent with the rain type detected by PR (shown in Table 1 and Figure 3). This is an important improvement over the TMI-only estimates, which gives a median convective fraction of 0.59. The TMI-only estimates are unrealistically low, especially since PR identifies almost all the pixels in CAT3 as convective. Differences between the TMI-only and TMI-LIS estimates are very small for CAT0, but increase for each successive lightning category. This finding is realistic since we expect the addition of lightning observation to be most beneficial where the lightning is most active.

### 4.2. Evaluation

[26] Rain rate retrievals using equation (1) with convective fraction estimates using equation (2) from TMI only and TMI-LIS are compared. We use a different TRMM data set for the evaluation (January 2006 to December 2009) to provide an independent sample. Figure 4 shows the frequency distribution of TMI-only and TMI-LIS convective fraction estimates for the TRMM PR defined convective and stratiform pixels. For convective pixels (P(C) = 1), the TMI-LIS algorithm estimates higher convective fractions than TMI only. TMI and LIS jointly identifies ~10% more pixels as completely convective (convective fraction = 1) than TMI only. For stratiform pixels, the TMI-LIS algorithm estimates marginally lower convective fractions. Table 4 summarizes the impact of CSI from using LIS information in conjunction with TMI, and provides the mean biases and root-mean-square (RMS) errors for the TMI-only and TMI-LIS estimates relative to PR. There is a very small improvement between the TMI-only and TMI-LIS algorithm for stratiform pixels without lightning, the bias and random error change from 0.10 to 0.09 and 0.15 to 0.13, respectively. For the rare occasions where LIS flashes are detected in stratiform rain (occurs in ~1.5% of stratiform pixels), the TMI-LIS algorithm misidentifies stratiform as convective due to the presence of lightning, and thus overestimates CSI compared to the TMI-only algorithm. For convective pixels (when PR convective fraction is 1), the mean CSI bias and random error for TMI-LIS are reduced by ~8% and ~2% from the TMI-only algorithm, respectively. For the LIS flash category CAT0, the CSI estimates from TMI-LIS are similar to the TMI-only estimates. However, for the other three LIS flash categories (CAT1, CAT and CAT2) The TMI-LIS CSI estimates are significantly improved compared to TMI-only CSI estimates. For example, for the highest lightning category CAT3, TMI-LIS virtually identifies all the pixels are convective (mean bias and RMS error are 0 and 0.01, respectively), while the TMI-only algorithm significantly underestimates the convective fraction (mean bias and RMS error are ~0.39 and 0.43, respectively).

[27] The impact of using LIS information in the rain rate retrievals also can be investigated using variation of convective fraction estimates as a function of TMI $T_b85V$ (Figure 5). Both TMI and TMI-LIS convective fraction estimates decrease monotonically with increasing $T_b85V$ (Figure 5a). PR estimates follow a similar pattern, but the convective fraction is fairly constant below 160 K. TMI-only algorithm generally underestimates convective fraction compared to PR, which is most apparent in the ~150 K to 200 K $T_b85V$ range. The TMI-LIS estimates are a significantly better match to the PR estimates in the 160 K to 210 K $T_b85V$ range; however, for $T_b85V$ values below 160 K (only ~1% of all pixels), the TMI-LIS algorithm tends to underestimate the convective fraction. Thus, the TMI-LIS algorithm slightly underestimates the convective fraction (and consequently rain rate) at intermediate $T_b85V$ ranges, and overestimates it at low Tb values. Conversely, TMI-only

### Table 2. Coefficients for TMI Convective Predictors for Different Lightning Categories in Equation (2)

<table>
<thead>
<tr>
<th></th>
<th>TB10V</th>
<th>Mean (TB37V,85V)</th>
<th>NPOL</th>
<th>STDEV</th>
<th>MINIMA</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMI</td>
<td>0.0028</td>
<td>−0.0004</td>
<td>0.0032</td>
<td>0.0081</td>
<td>0.0007</td>
<td>−0.6948</td>
</tr>
<tr>
<td>TMI-LIS CAT0</td>
<td>0.0022</td>
<td>0.0004</td>
<td>0.0032</td>
<td>0.0072</td>
<td>0.0006</td>
<td>−0.7439</td>
</tr>
<tr>
<td>TMI-LIS CAT1</td>
<td>0.0031</td>
<td>−0.0001</td>
<td>0.0026</td>
<td>0.0043</td>
<td>0.0010</td>
<td>−0.6053</td>
</tr>
<tr>
<td>TMI-LIS CAT2</td>
<td>0.0027</td>
<td>−0.0014</td>
<td>0.0018</td>
<td>0.0022</td>
<td>0.0008</td>
<td>0.0224</td>
</tr>
<tr>
<td>TMI-LIS CAT3</td>
<td>0.0002</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.0001</td>
<td>0.9119</td>
</tr>
</tbody>
</table>

### Table 3. Convective Fraction Estimates Using TMI-Only Information Compared With Estimates Using TMI-LIS Information for Different Lightning Categories

<table>
<thead>
<tr>
<th>Lightning Category</th>
<th>TMI Convective Fraction</th>
<th>TMI-LIS Convective Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5th Percentile</td>
<td>MEDIAN</td>
</tr>
<tr>
<td>CAT0</td>
<td>0</td>
<td>0.10</td>
</tr>
<tr>
<td>CAT1</td>
<td>0.11</td>
<td>0.41</td>
</tr>
<tr>
<td>CAT2</td>
<td>0.16</td>
<td>0.50</td>
</tr>
<tr>
<td>CAT3</td>
<td>0.24</td>
<td>0.59</td>
</tr>
</tbody>
</table>
consistently underestimates convective fraction across a wide $T_{b85V}$ range. For convective pixels, the mean rain rate bias relative is reduced from $\sim 17\%$ to $\sim 12\%$ by including LIS information with TMI. However, the random error for the TMI-LIS rain rate estimates is $\sim 4.5\%$ greater than the TMI-only estimates. This is presumably because the impact on RR biases is highly variable for the different LIS categories. The TMI-LIS algorithm significantly underestimates RR for CAT0, approximately matches the PR RR for CAT1, and severely overestimates RR for CAT2 and CAT3. This is because the $R_{\text{conv}}$ and $R_{\text{stra}}$ regressions from equation (1) generate the highest RRs for CAT2 and CAT3; since these categories contain a relatively high proportion of extremely low $T_{b85V}$ values (see Figure 3c). This finding suggests that recalculation of the $T_{b85V}$ – RR relationships for convective and stratiform precipitation that incorporates lightning information might increase the impact of lightning on PM rain rate algorithms, and will be a worthwhile follow-up study.

Figure 4. Frequency distributions of TMI and TMI-LIS convective fractions for convective pixels and stratiform pixels (as defined by PR) from January 2006 to December 2009.

Table 4. Mean Biases and RMS Errors Between TMI-Only and TMI-LIS CSI Relative to PR

<table>
<thead>
<tr>
<th>CSI</th>
<th>TMI – PR</th>
<th>TMI-LIS – PR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of Samples</td>
<td>Bias</td>
</tr>
<tr>
<td>All pixels</td>
<td>6 million</td>
<td>$-0.02$</td>
</tr>
<tr>
<td>Convective: all lightning categories</td>
<td>$\sim 850,000$</td>
<td>$-0.55$</td>
</tr>
<tr>
<td>Convective: CAT0</td>
<td>$\sim 575,000$</td>
<td>$-0.63$</td>
</tr>
<tr>
<td>Convective: CAT1</td>
<td>$\sim 125,000$</td>
<td>$-0.51$</td>
</tr>
<tr>
<td>Convective: CAT2</td>
<td>$\sim 80,000$</td>
<td>$-0.47$</td>
</tr>
<tr>
<td>Convective: CAT3</td>
<td>$\sim 75,000$</td>
<td>$-0.39$</td>
</tr>
<tr>
<td>Stratiform: All lightning categories</td>
<td>$\sim 3.8$ million</td>
<td>$0.10$</td>
</tr>
<tr>
<td>Stratiform: CAT0</td>
<td>$\sim 3.8$ million</td>
<td>$0.10$</td>
</tr>
<tr>
<td>Stratiform: CAT1, CAT2 and CAT3 combined</td>
<td>$\sim 55,000$</td>
<td>$0.30$</td>
</tr>
</tbody>
</table>
underestimates both rain rate and convective fractions near the convective core (versus PR estimates), whereas the TMI-LIS algorithm indicates higher convective fractions, and consequently greater rain rates in these areas. The mean PR rain rate for these convective regions is 14.1 mm/h, the mean TMI rain rate is 10.8 mm/h, and the mean TMI-LIS rain rate is 13.7 mm/h. Thus, using PR as the reference, this case reveals that the TMI-LIS algorithm is able to better represent rain rate and rain type delineation for convective cores. This improved identification of convective cores is most important in regions where most precipitation is associated with deep convection such as the region illustrated in this case.

5. Conclusions

[29] Tropical Rainfall Measuring Mission (TRMM) observations were analyzed to examine relationships between total lightning and precipitation measurements from satellite-borne microwave sensors. The main objective was to improve convective and stratiform delineation in microwave precipitation retrieval algorithms. This improvement was obtained by connecting the ice-phased microphysics as observed by both lightning and microwave instruments. The results of this study will provide a better microwave rain rate calibration target for the upcoming GOES-R rain rate (QPE) algorithm.

[30] PR rain type classification and surface rain rate estimates are treated in this study as the reference truth for TMI-only and TMI-LIS CSI and rain rate algorithm development and evaluation. (data from different periods of time for development and evaluation). PR rain measurements are widely accepted and deemed dependable. However, it needs to be noted that any errors in PR rain type classification and rain retrieval might propagate into TMI and TMI-LIS convective fraction estimates and rain retrievals. Given the nature of this study of developing satellite lightning-enhanced microwave convective areal fraction in rain rate retrieval, PR is the best option. Analysis of more than 14 million TRMM TMI/PR/LIS precipitation pixels over land reveals several important findings. In general, stratiform precipitation dominates when LIS detects no lightning, whereas the probability of convective precipitation increases with increasing lightning frequency. For tropical continents, lightning frequency increases with decreasing $Tb_{85V}$ and increasing radar reflectivity (i.e., both in the vertical structure and at the surface). Relationships between lightning occurrence (yes or no) and flash rates, $Tb_{85V}$, and radar reflectivity were examined to develop a simple convective probability classification scheme using four lightning flash rate categories (e.g., FR = 0, 0 < FR ≤ 1, 1 < FR ≤ 2, and FR > 2). Higher flash rate categories tend to have greater peak reflectivity (i.e., larger size ice particles), colder $Tb_{85V}$ (i.e., larger IWP), and greater surface reflectivity (i.e., higher surface rain rate). TMI Tbs first were stratified to the four lightning categories; multivariable linear regression was then applied to each lightning category to derive convective fraction estimates.

[31] TMI-only and TMI-LIS convective fraction estimates were then compared to examine the impact of including lightning information. Results reveal that the absence of lightning has a small positive impact on the identification of stratiform rain. Alternatively, the presence of lightning shows the most improvement for convective rain. Lightning information primarily improves the identification of PM convection fraction in the 0.4–1.0 range by correctly shifting TMI-only estimates from moderate to high convective fractions. TMI and LIS jointly identify 10% more pixels as completely convective. Overall, including lightning information in the CSI algorithm results in a 6% improvement for the entire range of rainfall. Thus, the multisensor approach in the

![Figure 5. (a) PR, TMI, and TMI-LIS convective fractions for all raining pixels from January 2006 to December 2009 as a function of TMI 85V Tb (in 10 K bins) along with (b) the number of pixels in each Tb bin.](image-url)
Figure 6. (left) RR and (right) convective fraction (P(C)) observed by PR and calculated with the TMI and TMI-LIS algorithm (top to bottom) for the same precipitating storm of Figure 1. Dashed lines delineate PR, TMI, and LIS coincident coverage.
GOES-R and GPM era, by leveraging information about precipitation-size ice and mixed-phase hydrometeors as observed by passive microwave, radar, and lightning sensors, will help enhance precipitation retrieval algorithms.

[12] Acknowledgments. This research was supported by NOAA GOES-R Risk Reduction (GOES-R3) program. The authors would like to acknowledge the guidance of Eric C. Bruning in the early stages of this study and thank Scott Rudolfsy for very useful suggestions on the manuscript.

References


