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The Role of GPS Precipitable Water Vapor and Atmosphere Stability Index in the Statistically Based Rainfall Estimation Using MTSAT Data

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ABSTRACT

A rainfall estimation method was developed based on the statistical relationships between cloud-top temperature and rainfall rates acquired by both the 10.8- μm channel of the Multi-Functional Transport Satellite (MTSAT) series and the Automated Meteorological Data Acquisition System (AMeDAS) C-band radar, respectively. The method focused on cumulonimbus (Cb) clouds and was developed in the period of June–September 2010 and 2011 over the landmass of Japan and its surrounding area. Total precipitable water vapor (PWV) and atmospheric vertical instability were considered to represent the atmospheric environmental conditions during the development of statistical models. Validations were performed by comparing the estimated values with the observed rainfall derived from the AMeDAS rain gauge network and the Tropical Rainfall Measuring Mission (TRMM) 3B42 rainfall estimation product. The results demonstrated that the models that considered the combination of total PWV and atmospheric vertical instability were relatively more sensitive to heavy rainfall than were the models that considered no atmospheric environmental conditions. The use of such combined information indicated a reasonable improvement, especially in terms of the correlation between estimated and observed rainfall. Intercomparison results with the TRMM 3B42 confirmed that MTSAT-based rainfall estimations made by considering atmospheric environmental conditions were more accurate for estimating rainfall generated by Cb cloud.

1. Introduction

Geostationary satellites make frequent observations with continuous spatial coverage, providing useful information for rainfall monitoring and the early warning of storms (Feidas and Cartalis 2001; Wardah et al. 2008). Thermal infrared data (TIR) centered at 10.8 μm are commonly used to detect cloud-top temperature for use in rainfall estimation (Haile et al. 2010). Lower temperatures are assumed to correspond to relatively cold and thick clouds, which tend to produce high rainfall intensity (Kuligowski 2003). However, clouds are essentially opaque to TIR, which cannot reveal the vertical profile of clouds that produce rainfall. To complement TIR data, microwave (MW)-based rainfall estimations are used, as MW radiation has the ability to penetrate clouds, thus allowing for a more direct measurement of

the rainfall column and vertical cloud structure. Several well-known algorithms have advantages when using complementary information in TIR and MW data, such as the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Sorooshian et al. 2000) and the Tropical Rainfall Measuring Mission (TRMM) 3B42 algorithm (Huffman et al. 2007). These products are easily accessible through their dedicated server via the Internet and can be used for water resource management purposes. However, the products are mainly delivered at 0.25° and 3-hourly spatial and temporal resolutions, respectively, which are relatively too coarse for certain hydrologic applications such as the detection of flash floods in small ungauged catchments. The aim of this study is to develop a rainfall estimation method based on a combination of TIR and MW that can be applied for the monitoring of flash floods; hence, rainfall information with high temporal resolution is necessary.

To combine TIR and MW for rainfall estimation, a statistical model that represents the relationship between them is commonly implemented (Vicente et al. 1998; Haile et al. 2010; Kinoti et al. 2010). Rainfall estimation

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using a TIR and MW statistical model as a function of TIR is considered to be suitable for convective clouds, but not suitable for nonconvective clouds (Kuligowski 2003). For separating convective and nonconvective clouds, cloud classification data should be considered during the development of the TIR and MW statistical model (Suseno and Yamada 2011). However, the use of a single statistical model for the estimation of rainfall is limited because of the variety of physical processes associated with rainfall generation, which eventually influences the relationship between cloud-top temperature and rainfall rates (Vicente et al. 1998).

According to Doswell et al. (1996), deep moist convection normally occurs during the warm season, when high moisture content is possible and buoyant instability promotes strong upward vertical motions. In this study, precipitable water vapor (PWV) and atmospheric vertical instability, both of which are related to the development of deep convective clouds, were investigated. The objectives of the study were to assess how a combination of total PWV and atmospheric vertical instability conditions improves TIR-based rainfall estimations using a statistical model by focusing on cumulonimbus (Cb) cloud systems and to validate the estimated rainfall by comparison with observed rainfall during convective storm rainfall events.

2. Study area and materials

The study area was Japan and its surrounding area within 30°–50°N, 120°–150°E (window size 20° × 30°). The two time periods examined were June–September of 2010 and 2011.

The collocated data pairs (i.e., obtained in the same geographical area during the same time periods) of TIR and MW were used to develop a statistical model for the estimation of rainfall. TIR images were acquired from the Multi-Functional Transport Satellite (MTSAT), particularly from the 10.8- μm channel (T_{IR1}). The MW-based rainfall rate observations were derived from the Automated Meteorological Data Acquisition System (AMeDAS) C-band radar data (RR). The 12.0- μm MTSAT image channel (T_{IR2}) was used in conjunction with T_{IR1} to develop a cloud-type classification system and cloud height images. In the study region, the spatial resolution of MTSAT data was approximately 5 × 5 km. The temporal resolutions of the MTSAT and C-band radar data were 1 h and 10 min, respectively.

Relative humidity derived from rawinsonde data is suitable to represent the moisture factor and was used by Vicente et al. (1998). However, such data have limitations in their spatial and temporal sampling. Therefore, we used a PWV estimated from ground-based GPS

networks to represent the total PWV. These data can offer spatiotemporal improvements in moisture observation when compared with radiosonde observations (Iwabuchi et al. 2006). GPS-PWV data are point-based measurements that represent the total atmospheric water vapor contained in a vertical column of unit area. GPS-PWV data have a temporal resolution of 10 min and are acquired by more than 1200 stations, giving a mean spacing of about 17 km across the land area of Japan.

To represent atmospheric vertical instability, the Showalter stability index (SSI) was used. The SSI's computation relies on vertical temperature profile information provided by a mesoscale model from the Japan Meteorological Agency (JMA; Saito et al. 2006). These data have a 3-hourly temporal resolution and are provided at 0000, 0300, 0600, 0900, 1200, 1500, 1800, and 2100 UTC. The spatial resolution of these datasets is approximately 0.1°.

For validation purposes, we compared the estimated rainfall with hourly AMeDAS-observed rainfall data. The TRMM 3B42 rainfall estimation data product (Huffman et al. 2007) that has a spatial and temporal resolution of 0.25° × 0.25° and 3 hourly, respectively, was also used as a reference for performing an inter-comparison with the rainfall estimation result.

3. Methods

To retrieve the rainfall from TIR, statistical relationships between the cloud-top temperature and rainfall rates derived from T_{IR1} and RR, respectively, were developed. To determine a collocated data pair between T_{IR1} and RR, because the AMeDAS C-band radar has a 10-min temporal resolution, instantaneous rainfall data were selected every 30 min from the AMeDAS C-band radar. Here we extracted T_{IR1} only for Cb cloud systems. A cloud classification method developed by Suseno and Yamada (2012) was employed to discriminate Cb from other cloud types. This cloud classification method uses an upper threshold in two-dimensional spectral spaces (T_{IR1} versus $\Delta T_{\text{IR1-IR2}}$) to define the Cb cloud type, that is, 2 K for $\Delta T_{\text{IR1-IR2}}$ and 225 K for T_{IR1} . Consequently, the statistical model developed can be used only for $T_{\text{IR1}} < 225$ K.

Before developing the statistical relationships, a parallax correction must be performed on the MTSAT images (both T_{IR1} and T_{IR2}). We followed the parallax correction procedures used by Vicente et al. (2002). The principle of this algorithm is to relocate the apparent position of the cloud on the Earth based on the cloud height at its correct geographical location, relative to the MTSAT satellite height and position. The cloud height information was estimated from the MTSAT images according to

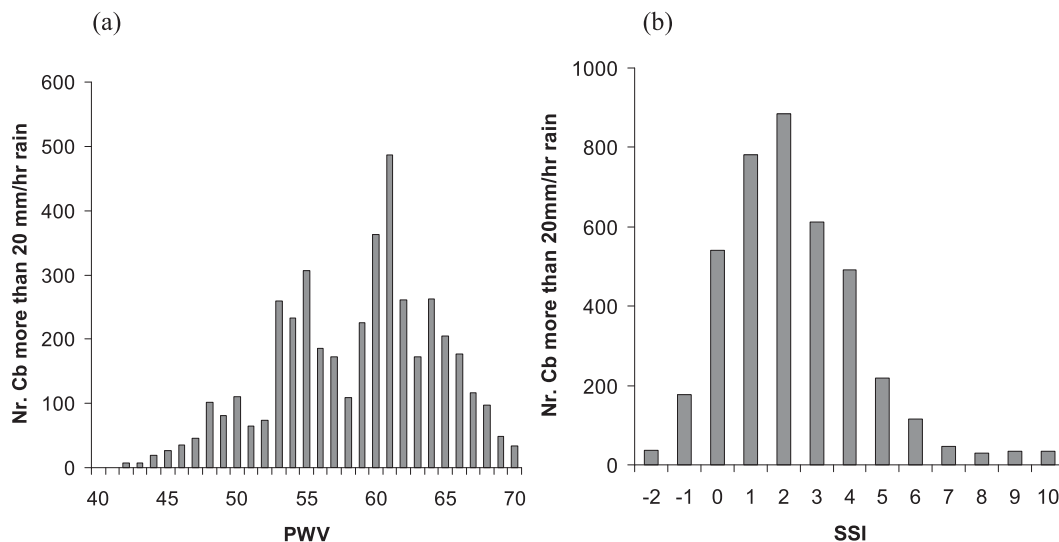


FIG. 1. Histogram showing the frequency of Cb pixels that produce high rainfall intensity ($>20 \text{ mm h}^{-1}$) according to (a) GPS-PWV levels and (b) SSI levels.

a method developed by Hamada and Nishi (2010). The cloud height estimation method also utilized T_{IR1} versus $\Delta T_{\text{IR1-IR2}}$ spectral space, trained by *CloudSat*. The parallax-corrected MTSAT images that resulted from this process were used to generate further statistical relationships including rainfall retrieval processes.

The T_{IR1} and RR statistical relationships differ depending on the availability of precipitable water vapor and the atmospheric vertical instability during the development of convective clouds. Several atmospheric situations were considered to investigate the characteristics of the T_{IR1} and RR statistical relationships, that is, considering only water vapor availability (PWV), considering only atmospheric vertical instability (SSI), and considering a combination of water vapor availability and atmospheric vertical instability (CMB). The T_{IR1} and RR statistical relationships obtained under these conditions were evaluated by comparing them with the T_{IR1} and RR statistical relationships without considering any atmospheric environmental conditions (ORG).

The T_{IR1} and RR data pairs were acquired from the collocated images to create a modified exponential model, which was formulated as follows:

$$\text{RR} = ae^{b/T_{\text{IR1}}}, \quad (1)$$

where a and b are the regression coefficients and e is the natural log. The parallax correction described above was performed mainly to define the correct geographic location of the clouds. However, offset errors due to time and navigation differences between MTSAT and AMeDAS C-band radar still remain. Temporal averaging was

applied to minimize the effect of such offset errors on rainfall estimation. Temporal averaging was applied to RR for equal T_{IR1} classes with 1° Kelvin intervals. For each T_{IR1} class interval, the RR was averaged and assigned to the corresponding T_{IR1} to match the MTSAT data (Vicente et al. 1998; Kinoti et al. 2010).

Twenty-eight convective systems over the land area of Japan during the period of June–September 2010 and June–August 2011 were recognized by visually inspecting the T_{IR1} image, followed by a cloud classification using the Suseno and Yamada (2012) algorithm. Furthermore, the GPS-PWV and SSI that represented the atmospheric environmental situations corresponding with those convective storm events were obtained based on those with the closest acquisition time to the collocated T_{IR1} image. The instantaneous GPS-PWV data at the 30-min acquisition were chosen, whereas the SSI data at 3-hourly intervals that were the closest to the collocated T_{IR1} image were utilized. A resampling procedure was conducted for GPS-PWV and SSI data using the same georeference as the T_{IR1} image to ensure that the maps spatially matched each other.

We identified the level at which the total PWV as well as atmospheric vertical instability influenced the rainfall intensity to the greatest extent. Figures 1a and 1b show a frequency histogram of the accumulated number of Cb pixels that produced high rainfall rates ($>20 \text{ mm h}^{-1}$) against the GPS-PWV and SSI levels, respectively, from the 28 storm cases over the land area of Japan. Two peaks are observed around 55 and 61 mm, which are where the highest rainfall intensity occurred under these PWV conditions. A threshold value around 58 mm was

determined to separate the PWV condition that most influenced high-intensity rainfall. A similar analysis for SSI was performed to identify the value for which SSI most contributed to high rainfall intensity. Figure 1b shows that high rainfall intensity mostly occurred for an SSI around +2. Here we consider that an $SSI \leq +2$ is a relatively unstable condition that produces convective storms. To discriminate atmospheric situations that eventually influence the characteristic T_{IR1} and RR statistical relationships, a value of 58 mm for GPS-PWV and +2 for SSI are proposed as threshold values.

Eight modified exponential models were developed according to T_{IR1} and RR data pairs, which were discriminated based on predefined atmospheric environmental situations, that is, models that consider only PWV and SSI, namely, PWV1 ($GPS\text{-}PWV \geq 58$ mm), PWV2 ($GPS\text{-}PWV < 58$ mm), SSI1 ($SSI \leq +2$), and SSI2 ($SSI > +2$), and models that combine GPS-PWV and SSI, namely, CMB1 ($GPS\text{-}PWV \geq 58$ mm and $SSI \leq +2$), CMB2 ($GPS\text{-}PWV < 58$ mm and $SSI \leq +2$), CMB3 ($GPS\text{-}PWV \geq 58$ mm and $SSI > +2$), and CMB4 ($GPS\text{-}PWV < 58$ mm and $SSI > +2$). For purposes of comparison, one model (ORG) that did not consider any environmental variable was also generated.

The estimated rainfall was calculated based on T_{IR1} by applying a suitable T_{IR1} and RR statistical model matched with the current atmospheric environmental situation. The performance of rainfall estimations made by considering and not considering atmospheric environmental conditions was measured by comparing with observed rainfall on a pixel-to-pixel basis in a window box $1^\circ \times 1^\circ$ in size. Here the pixel values of estimated rainfall and their corresponding observed rainfall contained in this $1^\circ \times 1^\circ$ window box were compared. An incompatible spatial domain exists between rainfall observations (obtained as point data) and satellite-based precipitation records (captured as grid data), and therefore, the point-based rainfall observations were transformed into the area domain by using an inverse distance-weighting interpolation (Haile et al. 2010). The averaging process during interpolation also minimizes the geolocation error.

The estimation of the rainfall was evaluated by statistical tests, that is, the correlation coefficient r , bias, and root-mean-square error (RMSE), which are defined as follows (Ebert 2007):

$$r = \frac{\sum_{i=1}^N (E_i - \bar{E})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^N (E_i - \bar{E})^2} \sqrt{\sum_{i=1}^N (O_i - \bar{O})^2}} \quad (\text{perfect score} = 1), \quad (2)$$

$$\text{bias} = \frac{1}{N} \sum_{i=1}^N (E_i - O_i) \quad (\text{perfect score} = 0), \quad \text{and} \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (E_i - O_i)^2} \quad (\text{perfect score} = 0), \quad (4)$$

where E_i and O_i are the estimated and observed rainfall of i th data, $\bar{E}$ and $\bar{O}$ are the average values of the estimated and observed rainfall, and N is the number of data points recorded during the period that a Cb was detected.

An intercomparison between the statistical models and the TRMM 3B42 datasets was also conducted. TRMM 3B42 provides the best estimates of precipitation in each grid box for each observation time (Huffman et al. 2007). Because it was delivered at 3-hourly temporal resolution, the instantaneous MTSAT estimated rainfall that was closest to the TRMM 3B42 was chosen for this comparison. A process of resampling into TRMM 3B42 (spatial resolution $0.25^\circ \times 0.25^\circ$) was performed to ensure that they were spatially comparable to the estimated rainfall datasets. TRMM 3B42 is not only detecting convective rainfall but also all other types of rainfall that could be observed; therefore, the comparison was performed only for the resampled MTSAT pixels that contained 100% Cb cloud type. The resampling process was also conducted on the interpolated rainfall observation map. For the intercomparison purpose, a pixel-to-pixel-based comparison within a $1^\circ \times 1^\circ$ window box was also adopted. This means that each pixel value from both TRMM 3B42 and MTSAT estimated rainfall after resampling was compared with the resampled observed rainfall map within the $1^\circ \times 1^\circ$ window box.

4. Results and discussion

An example of T_{IR1} on 29 June 2010 at 0132 UTC over part of Kyushu Island, Japan (see the box area in Fig. 2a), before and after parallax correction is shown in Figs. 2b and 2c, respectively. The figures represent the distribution of cloud-top temperature values, while the white gaps in between the pixels in the parallax-corrected image represent the distance of cloud displacement. The collocated AMeDAS C-band radar data (black dots) are overlaid onto them. The T_{IR1} before the parallax correction (see the dashed yellow area in Fig. 2b) indicates the presence of some relatively warmer cloud pixels that correspond with relatively high rainfall rates (denoted by relatively larger black dots). Furthermore, after applying the parallax correction (see the dashed yellow area in Fig. 2c), the location of these warm pixels is

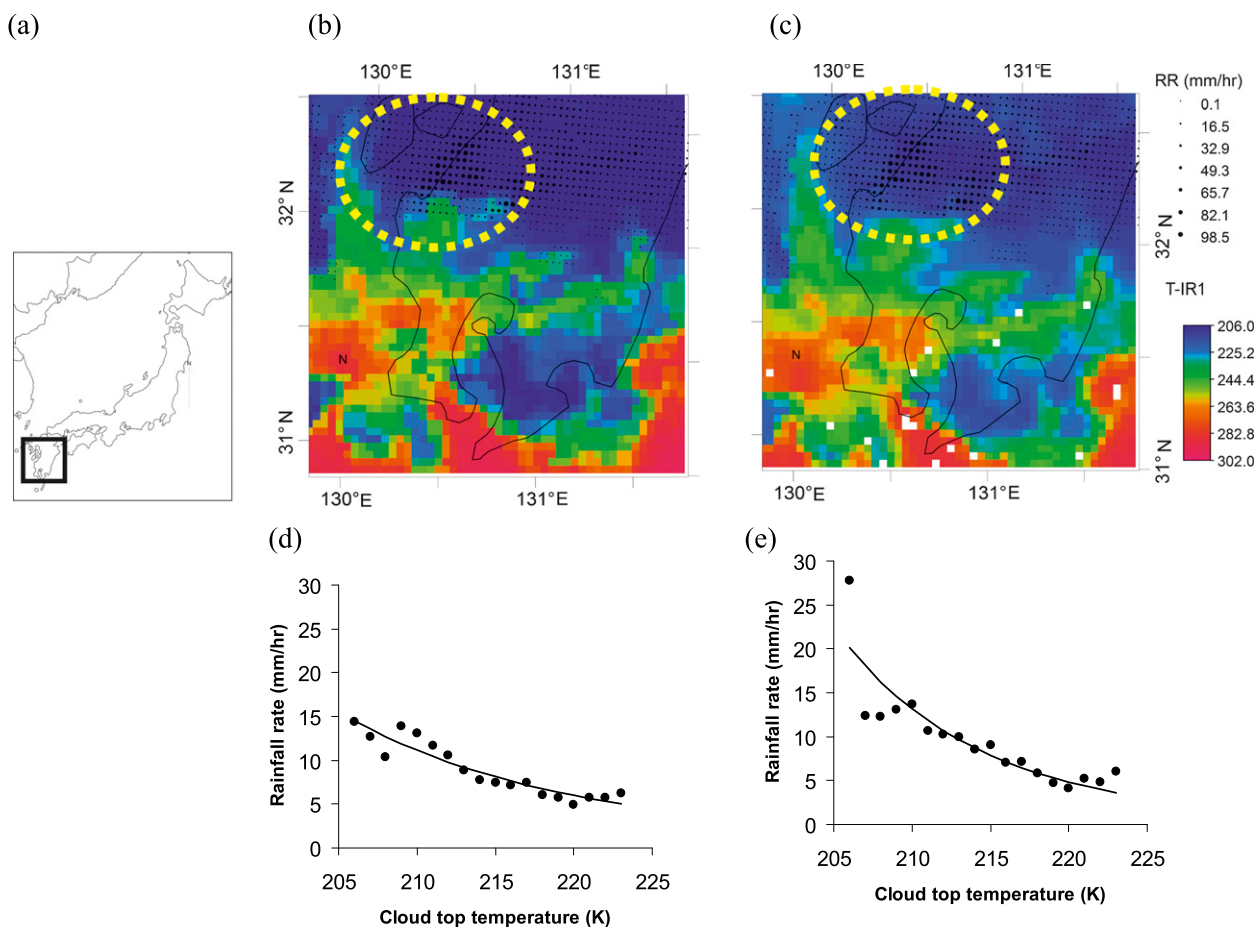


FIG. 2. (a) An example of the parallax correction on MTSAT IR1 data over part of Kyushu, Japan, at 0132 UTC 29 June 2010, (b) an MTSAT IR1 image before parallax correction, and (c) an MTSAT IR1 image after parallax correction. The small black dots over the images are rainfall rates observed by AMeDAS C-band radar. The graphs under the figures represent the statistical relationship of cloud-top temperature and rainfall rates used to produce the collocated MTSAT IR1 images and C-band radar rainfall rate values (d) before and (e) after parallax correction.

shifted and replaced by the adjacent colder pixels. Those colder cloud pixels are closely matched with the corresponding high rainfall rates. This confirms the assumption that the lowest cloud-top temperature is associated with higher rainfall rates. This is also indicated by the statistical relationship between T_{IR1} before and after the parallax correction with RR, as shown in Figs. 2d and 2e, respectively. Although these figures confirm the assumption, the image without the parallax correction fails to capture relatively high rainfall rates that should correspond with lower cloud-top temperatures.

Figures 3a–h show modified exponential regression curves for different atmospheric environmental conditions. The regression line obtained by the model that considers total PWV or atmospheric vertical instability as well as their combination (solid line) is plotted together with the model without considering atmospheric conditions (dashed line). The scattered points shown in Figs. 3a–h

are the average rainfall rates for every 1-K cloud-top temperature interval. The error bar for each point represents the 95% confidence interval (CI), which is estimated using

$$\text{CI} = \bar{R} \pm \left(1.96 \frac{\sigma}{\sqrt{n}} \right), \quad (5)$$

where $\bar{R}$ and σ are the mean and standard deviation, respectively, of the C-band radar rainfall rates at each 1-K temperature interval and n is the number of data points at each temperature interval (Haile et al. 2010). The confidence intervals become relatively wider for low cloud-top temperature values. Wider confidence intervals are most probably due to rare storm events that correspond to low cloud-top temperature during the study periods. This situation produces only a few data points for lower cloud-top temperature values compared with the higher temperature values.

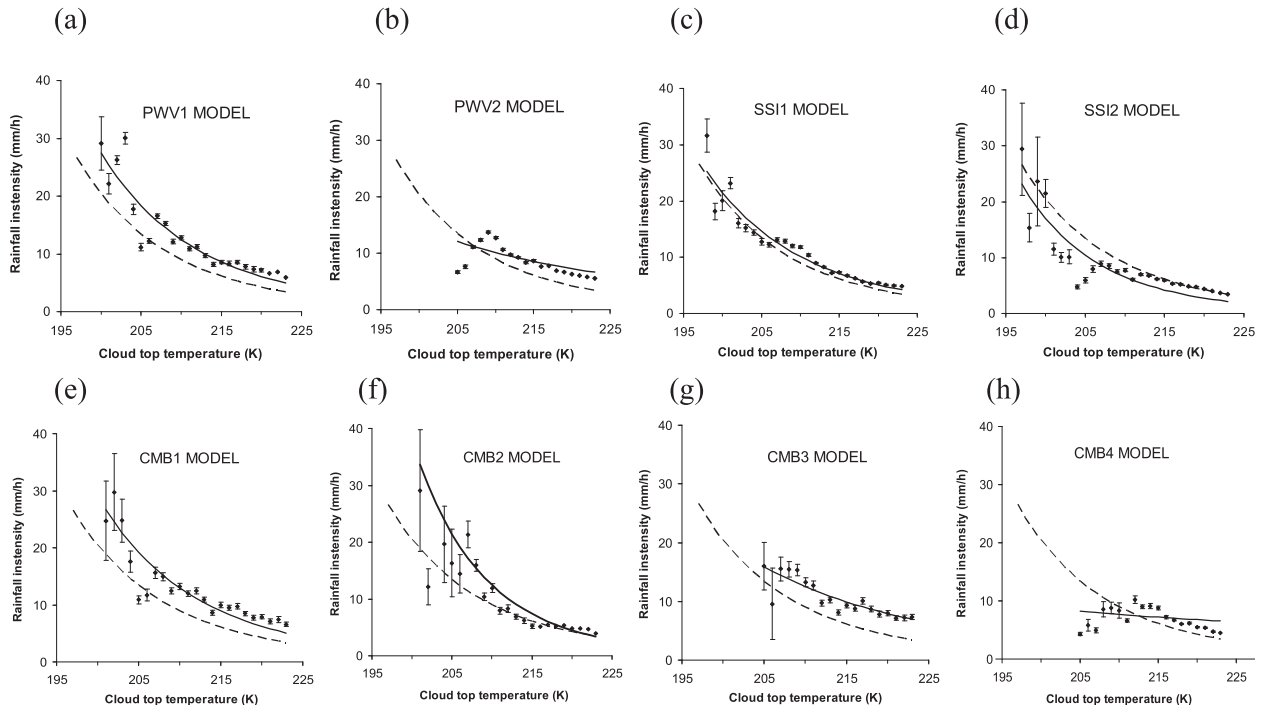


FIG. 3. The modified exponential regression models corresponding to different atmospheric environmental conditions: (a) PWV1, (b) PWV2, (c) SSI1, (d) SSI2, (e) CMB1, (f) CMB2, (g) CMB3, and (h) CMB4 (solid line) compared to the model without considering atmospheric environmental conditions (ORG; dashed line).

According to Fig. 3a, a high rainfall rate can be produced only by relatively high PWV conditions (≥ 58 mm) at T_{IR1} around 200 K. For the relatively low PWV conditions (< 58 mm) shown in Fig. 3b, the model can only estimate a lower rainfall intensity up to a cloud-top temperature around 205 K. This implies that total PWV contributes strongly to the generation of high rainfall rates. Figures 3c and 3d show the regression curves generated by relatively unstable ($SSI < +2$) and stable ($SSI > +2$) atmospheric situations, respectively. Both regression curves almost coincide with the regression curve for the situation without consideration of atmospheric conditions. However, when we examine Fig. 3d more carefully, it can be seen that some heavy rainfall events occur under relatively stable atmospheric conditions. Even though the number of such events is small (indicated by the wide confidence interval), they influence the shape of the regression line. One of the reasons for this condition is the limitations in spatial and temporal resolution of SSI. A relatively coarse spatial resolution would lead to an SSI that does not adequately separate the high and low rainfall rates corresponding to the atmospheric vertical instability conditions. A low temporal resolution results in spatial shifting between rainfall and the SSI because of the time discrepancy during data acquisition. Figures 3e–h show the regression curves for the situation where total PWV and atmospheric vertical

instability are combined. The figures indicate that the specific situation for combined total PWV and atmospheric vertical instability can be represented by different regression curves.

Before moving to the next stage (i.e., to measure the performance of MTSAT rainfall estimation by comparing the results with observed rainfall), a cross-correlation analysis was conducted to determine the lag time between them. The grid values at the coordinate locations of station 74181 ($33^{\circ}33'59''N$, $133^{\circ}32'48''E$) and station 87321 ($32^{\circ}13'52''N$, $131^{\circ}9'2''E$) were extracted from hourly estimated and observed rainfall data during the period of 16–20 September 2011. Figures 4a and 4b show the cross correlograms of estimated rainfall (colored bars) and observed rainfall for both locations. These figures indicate a 1-h time lag between estimated and observed rainfall, which implies that the rainfall detected by satellite could be observed as real rainfall by a rain gauge after 1 h.

The performance of the statistical models was tested in three case studies: 1) at 0630–1330 UTC 22 June 2010 over Kyushu island (beginning of summer; hereafter case A), 2) at 1532–2132 UTC 24 August 2011 over Nara prefecture (middle of summer; hereafter case B), and 3) at 1732–0532 UTC 19–20 September 2011 over Kyushu island (end of summer; hereafter case C). Figure 5a shows the locations of these three case studies; each location is bounded by a $1^{\circ} \times 1^{\circ}$ window box.

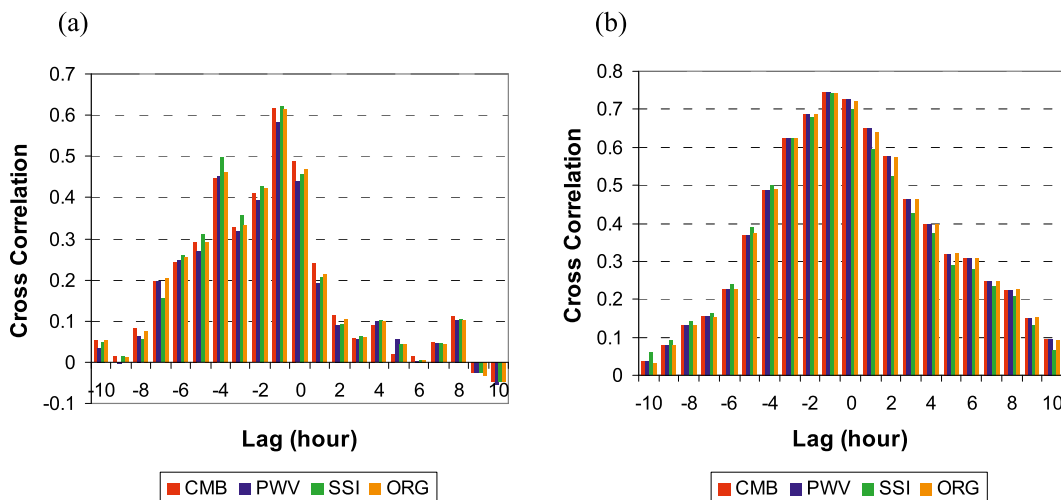


FIG. 4. Cross correlograms of estimated and observed rainfall for (a) station 74181 and (b) station 87321. In both cases, the maximum correlation occurs at a time lag of -1 h.

To show the difference among statistical models, a snapshot of the rainfall during the peak of a heavy rainfall event at 1130 UTC 22 June 2010 over Kyushu island, Japan (case A), was estimated using the model

without consideration of any atmospheric conditions (Fig. 5b), the model considering only PWV (Fig. 5c), the model considering only SSI (Fig. 5d), and the model considering both PWV and SSI (Fig. 5e). As

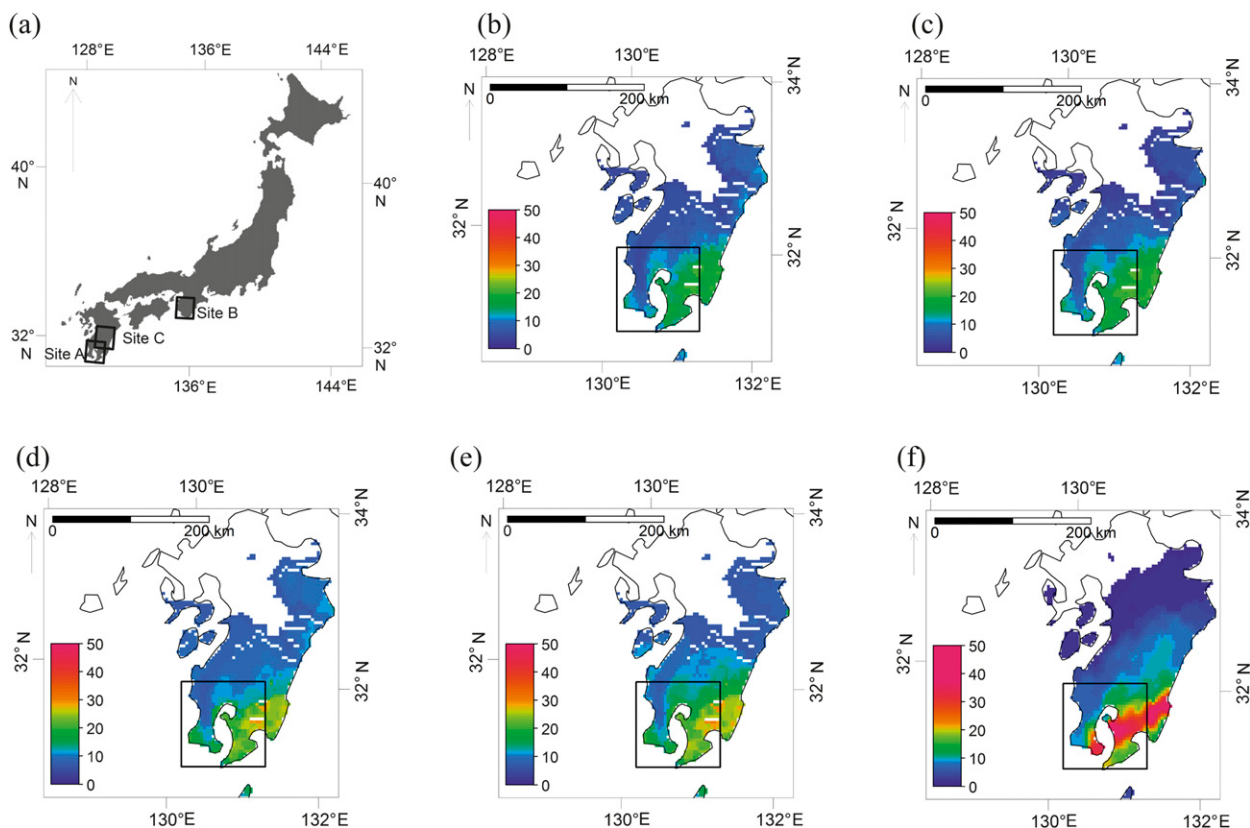


FIG. 5. (a) Locations of three case studies are shown by $1^\circ \times 1^\circ$ window boxes. Snapshots of heavy rainfall event distribution from 22 June 2010 at 11:30 UTC over Kyushu, Japan: Estimated rainfall (b) without considering atmospheric environmental condition (ORG); (c) considering only SSI; (d) considering only PWV; (e) considering both atmospheric vertical instability and precipitable water vapor (CMB); and (f) observed (OBS).

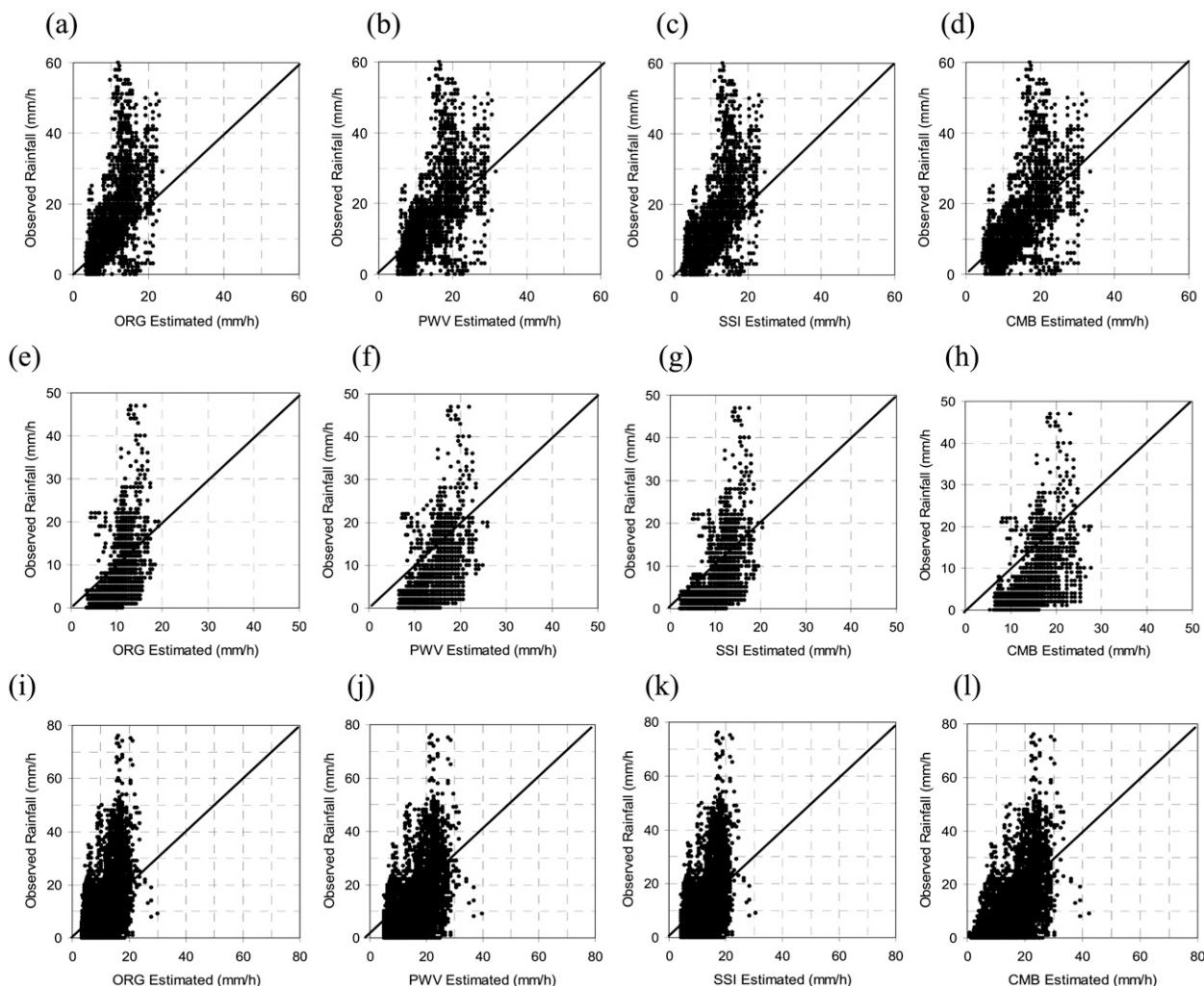


FIG. 6. Scatterplot of hourly observed rainfall vs MTSAT rainfall estimation (a),(e),(i) without considering atmospheric environmental conditions, (b),(f),(j) considering only PWV, (c),(g),(k) considering only SSI, and (d),(h),(l) considering both PWV and SSI, for cases (top) A, (middle) B, and (bottom) C.

explained above, there was a 1-h time lag between estimated rainfall and observed rainfall; therefore, the estimated rainfall results were compared with interpolated observed rainfall (Fig. 5f) for the following hour (i.e., 1230 UTC). Compared with the observed rainfall, MTSAT rainfall estimations did not represent local strong rainfall events very well, even though in the wider spatial domain, they provided a reasonable representation of the spatial distribution of rainfall. This situation is confirmed by Figs. 6a–d, which show hourly scatterplots of observed rainfall versus MTSAT rainfall estimations without considering the atmospheric environmental conditions, considering only the PWV, considering only the SSI, and considering both PWV and SSI for case A. For rainfall $>30 \text{ mm h}^{-1}$, MTSAT rainfall estimations fail to represent such high rainfall

rates. However, compared with the ORG model, a consideration of the atmospheric environmental information, particularly the combination of SSI and PWV, could enhance the estimated rainfall. It can be seen in Figs. 6a, 6e, and 6i that the maximum estimated rainfall is around 20 mm h^{-1} . Therefore, it can be increased up to around 25 mm h^{-1} , as shown by Figs. 6d, 6h, and 6l. This indicates that the use of combinations of atmospheric conditions is more sensitive for detecting the high rainfall rates produced by low cloud-top temperatures.

Table 1 describes the statistical performance between the model considering atmospheric environmental conditions and the model that does not consider the atmospheric environmental conditions. The figures were calculated by considering the 1-h time lag between the estimated and observed rainfall. The table indicates that

TABLE 1. Comparison of the T_{IR1} and RR statistical models considering total PWV and atmospheric vertical instability (CMB, PWV, and SSI) and the model without considering total PWV and atmospheric vertical instability (ORG) for cases A, B, and C. Boldface numbers show the best statistical results.

	Case A				Case B				Case C			
	Sample size	r	Bias (mm h^{-1})	RMSE (mm h^{-1})	Sample size	r	Bias (mm h^{-1})	RMSE (mm h^{-1})	Sample size	r	Bias (mm h^{-1})	RMSE (mm h^{-1})
CMB	3588	0.66	1.0	8.6	4758	0.54	7.8	9.4	8975	0.54	4.6	9.9
PWV	3588	0.66	0.2	8.6	4758	0.51	4.7	7.0	10 484	0.51	5.7	10.8
SSI	3588	0.65	-2.4	9.2	4758	0.61	7.3	8.7	8475	0.61	0.9	8.9
ORG	3588	0.65	-3.0	9.5	4758	0.48	5.0	7.2	10 484	0.51	0.8	9.5

in terms of bias and RMSE, the use of atmospheric environmental conditions for rainfall estimation does not produce a meaningful improvement when compared to the model that does not consider any atmospheric environmental conditions. However, the model that considers the combination of total PWV and atmospheric vertical instability demonstrates a reasonable improvement in terms of correlation. This improvement in performance in terms of correlation supported the observation

that combinations of parameters are more sensitive in detecting high rainfall rates produced by low cloud-top temperatures, as explained in the paragraph above.

The results of an intercomparison between the MTSAT rainfall estimation and the TRMM 3B42 data product for cases A, B, and C are presented in Figs. 7a–e, 7f–j, and 7k–o, respectively. Their statistical performance is described in Table 2. As shown in Figs. 7a, 7f, and 7k, the scatterplots indicate that the TRMM 3B42

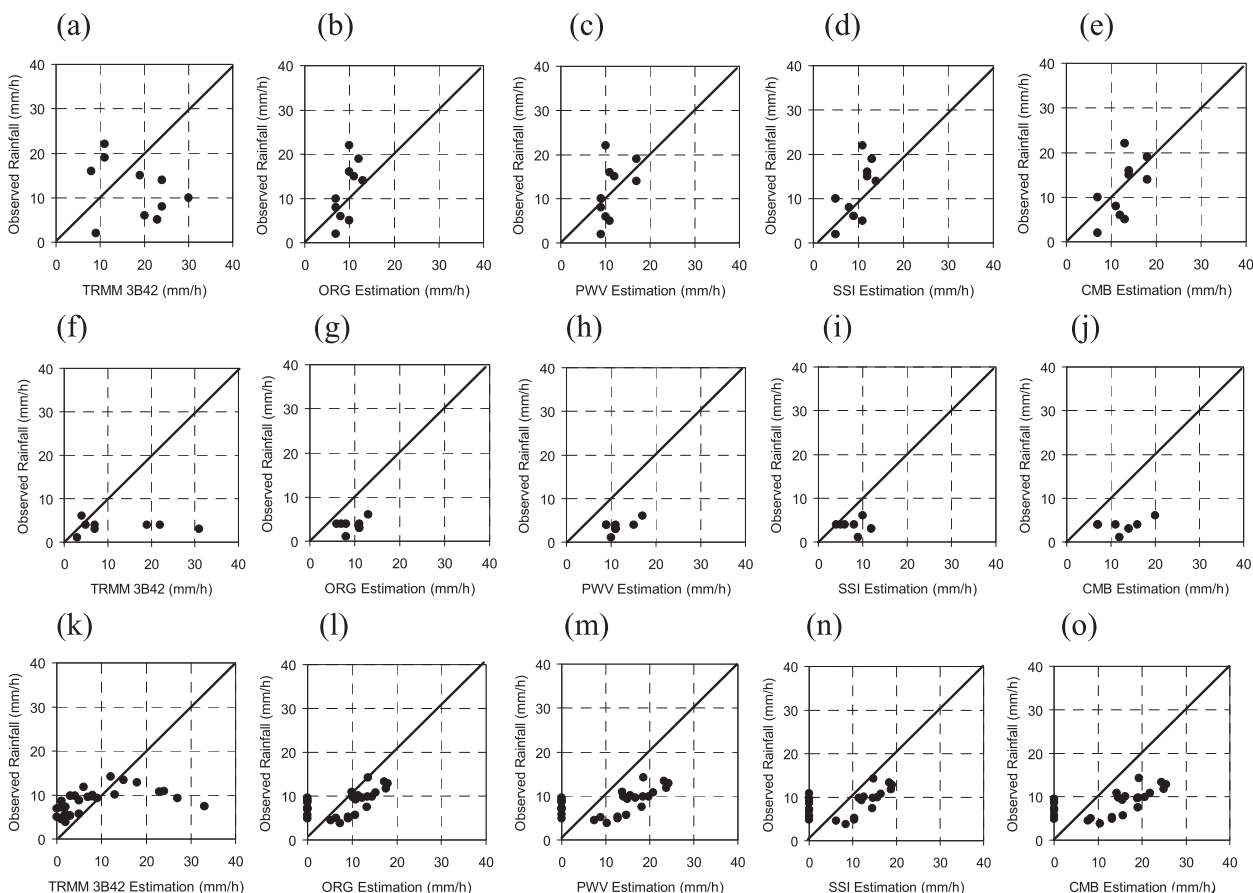


FIG. 7. Scatterplot of 3-hourly observed rainfall vs (a),(f),(k) TRMM 3B42, (b),(g),(l) MTSAT rainfall estimation without considering atmospheric environmental conditions, (c),(h),(m) considering only PWV, (d),(i),(n) considering only SSI, and (e),(j),(o) considering both PWV and SSI, for cases (top) A, (middle) B, and (bottom) C.

TABLE 2. Comparison of MTSAT IR1-based rainfall estimations considering and not considering total PWV and atmospheric vertical instability and the TRMM 3B42 rainfall estimation product for cases A, B, and C. MTSAT-CMB, MTSAT-PWV, and MTSAT-SSI refer to MTSAT IR1-based rainfall estimations considering the combination of PWV and SSI, PWV only, and SSI only. MTSAT-ORG refers to a MTSAT IR1-based rainfall estimation considering no atmospheric environmental conditions. Boldface numbers show best statistical results.

	Case A				Case B				Case C			
	Sample size	r	Bias (mm h^{-1})	RMSE (mm h^{-1})	Sample size	r	Bias (mm h^{-1})	RMSE (mm h^{-1})	Sample size	r	Bias (mm h^{-1})	RMSE (mm h^{-1})
MTSAT-CMB	10	0.62	1.0	5.0	8	0.32	9.0	9.8	28	0.55	3.1	8.4
MTSAT-PWV	10	0.48	-0.2	5.4	8	0.60	8.0	8.3	28	0.54	2.6	7.8
MTSAT-SSI	10	0.65	-1.7	5.1	8	-0.21	4.6	5.7	28	0.52	-1.2	6.4
MTSAT-ORG	10	0.64	-2.2	5.6	8	0.34	5.8	6.2	28	0.55	-0.4	5.3
TRMM 3B42	10	-0.33	6.2	12.6	8	-0.02	8.6	13.1	28	0.51	-0.1	7.8

data product was more scattered than MTSAT rainfall estimations for case A and was overestimated to a larger extent for cases B and C. These conditions were confirmed by the lower correlations than those for the MTSAT rainfall estimations (see Table 2). The bias and RMSE of TRMM 3B42 are also larger than the MTSAT rainfall estimations, except for case C. These results suggest that MTSAT rainfall estimations perform better than the TRMM 3B42 data product.

5. Conclusions

A method of rainfall estimation based on the statistical relationships between T_{IR1} and RR was developed for heavy rainfall generated by convective cloud in Japan and the surrounding area. T_{IR1} and RR data were acquired from MTSAT IR1 and AMeDAS C-band radar, respectively, for the periods of June–September 2010 and 2011. A parallax error correction was performed for the MTSAT datasets. To differentiate between convective and nonconvective cloud, the Suseno and Yamada (2012) algorithm cloud classification algorithm was applied to the parallax-corrected MTSAT datasets. The total PWV and atmospheric vertical instability conditions during the convection process, which influence the T_{IR1} and RR statistical relationships, were investigated. These atmospheric environmental conditions were represented by GPS-PWV and SSI, respectively. Values of 58 mm for GPS-PWV and +2 for SSI were proposed as thresholds for discriminating such atmospheric environmental conditions. Eight modified exponential models were developed according to T_{IR1} and RR data pairs, which were discriminated based on predefined atmospheric environmental situations, that is, models that considered only PWV and SSI, namely, PWV1 (GPS-PWV $\geq$ 58 mm), PWV2 (GPS-PWV < 58 mm), SSI1 (SSI $\leq$ +2), and SSI2 (SSI > +2), and models that combined GPS-PWV and SSI, namely, CMB1 (GPS-PWV $\geq$ 58 mm and SSI $\leq$ +2), CMB2 (GPS-PWV < 58 mm and SSI $\leq$ +2), CMB3

(GPS-PWV $\geq$ 58 mm and SSI > +2), and CMB4 (GPS-PWV < 58 mm and SSI > +2). One model, ORG, which did not consider GPS-PWV and SSI, was also generated.

Several different regression curves for the statistical relationships of T_{IR1} and RR were produced, especially by combining PWV and SSI conditions. Because of the occurrence of rare storm events that corresponded to low cloud-top temperatures during this study period, the confidence intervals of the statistical model became relatively wider for low cloud-top temperature values. When compared with the model that did not consider any atmospheric environmental conditions, the use of atmospheric environmental conditions for making rainfall estimations enhanced the accuracy of rainfall estimation, particularly when using the model that considered a combination of total PWV and atmospheric vertical instability, and eventually improved the performance, particularly in terms of correlation. However, MTSAT rainfall estimation was not successful in representing local heavy rainfall events, even though it performed reasonably well when predicting the rainfall spatial distribution at a wider spatial domain.

The intercomparison results between MTSAT IR1-based rainfall estimations and the TRMM 3B42 data product demonstrated that MTSAT IR1-based rainfall estimations either considering or not considering total PWV and atmospheric vertical instability produced a reasonably better performance than the TRMM 3B42 data product.

Because of the limitation of the number of samples that were used in this research, the full variety of physical processes associated with convective rainfall generation may not have been included. Therefore, more samples should be included in the development and validation of statistical models to reach a more definite conclusion.

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