Development of a Precipitation Climate Record from Spaceborne Precipitation Radar Data. Part I: Mitigation of the Effects of Switching to Redundancy Electronics in the TRMM Precipitation Radar

Kaya Kanemaru\textsuperscript{a} and Takuji Kubota

Earth Observation Research Center, Japan Aerospace Exploration Agency, Tsukuba, Japan

Toshio Iguchi

National Institute of Information and Communications Technology, Koganei, Japan

Yukari N. Takayabu

Atmosphere and Ocean Research Institute, University of Tokyo, Kashiwa, Japan

Riko Oki

Earth Observation Research Center, Japan Aerospace Exploration Agency, Tsukuba, Japan

(Manuscript received 6 February 2017, in final form 13 June 2017)

Abstract

Precipitation observation with the Tropical Rainfall Measuring Mission’s (TRMM’s) precipitation radar (PR) lasted for more than 17 years. To study the changes in the water and energy cycle related to interannual and decadal variabilities of climate, homogeneity of long-term PR data is essential. The aim of the study is to develop a precipitation climate record from the 17-yr PR observation. The focus was on mitigating the discontinuities associated with the switching to redundant electronics in the PR in June 2009. In version 7 of the level-1 PR product, a discontinuity in noise power is found at this timing, indicating a change in the signal-to-noise ratio. To mitigate the effect of this discontinuity on climate studies, the noise power of the B-side PR obtained after June 2009 is artificially increased to match that of the A-side PR. Simulation results show that the storm height and the precipitation frequency detected by the PR relatively decrease by 2.17% and 5.15% in the TRMM coverage area (35°S–35°N), respectively, and that the obvious discontinuity of the time series by the storm height and the precipitation fraction caused by the switching to the redundancy electronics is mitigated. Differences in the statistics of other precipitation parameters caused by the switching are also mitigated. The unconditional precipitation rate derived from the adjusted data obtained over the TRMM coverage area decreases by 0.90% as compared with that determined from the original data. This decrease is mainly caused by reductions in the detection of light precipitation.

1. Introduction

Precipitation observation from space utilizing the precipitation radar (PR) started for the first time with the Tropical Rainfall Measuring Mission (TRMM), which was...
The TRMM PR continuously collected precipitation data for more than 17 years until its termination on 1 April 2015 with a decline in the TRMM orbit altitude. On 28 February 2014, on the other hand, the Core Observatory of the Global Precipitation Measurement (GPM) mission was launched (Hou et al. 2014), and the GPM dual-frequency precipitation radar (DPR) started providing precipitation data succeeding the TRMM PR observation, with one year overlap of observations. The DPR consists of a Ku-band precipitation radar (KaPR, 13.6 GHz), which is similar to the PR (13.8 GHz), and a Ka-band precipitation radar (KaPR, 35.5 GHz). These radars adopt very similar designs but vary in terms of sensitivity, accuracy, and frequency, among others. PR and DPR not only estimate precipitation rate accurately over both land and the oceans but also provide adequate information to derive precipitation characteristics (e.g., storm top height and precipitation vertical profile). Homogeneity of long-term PR/DPR data is essential to study water cycle changes related to interannual variability and decadal change. Long-term precipitation datasets—that is, data spanning 20–30 years—estimated by infrared and microwave imagers are also available (e.g., Xie and Arkin 1997; Adler et al. 2003; Wentz et al. 2007). However, it is known that interannual variability of precipitation associated with El Niño–Southern Oscillation (ENSO) shows a large difference between the estimated rainfall from the TRMM PR and that from the TRMM microwave imager (TMI) (Robertson et al. 2003; Wang et al. 2008; Lau and Wu 2011). Differences in precipitation estimates were inferred to arise from the individual assumptions of each retrieval in previous studies (e.g., Masunaga et al. 2002; Ikai and Nakamura 2003; Shige et al. 2006), which indicate that uncertainty of algorithm assumptions by each sensor appears as differences in the interannual variability of precipitation. A difference in assumptions may also cause a difference in long-term precipitation variability derived from different sensors and algorithms so that an intercomparison of precipitation data is required to understand the plausible long-term precipitation variability.

The quality of the PR data obtained by the TRMM satellite was observed to change over the 17-yr observation period. For example, the PR data have discontinuities in quality associated with an increase in the TRMM satellite altitude (TRMM boost) in August 2001 and with the switching to redundant electronics in June 2009. The change in precipitation amount of the PR estimate attributed to the TRMM boost is evaluated as a decrease in the range from 5.9% to 8.8% (Wang et al. 2008; Shimizu et al. 2009) and is mostly caused by mainlobe contamination and beam mismatch correction errors; this change is interpreted as a bias of the angle-bin dependence (Shimizu et al. 2009; Hirose et al. 2012). At near-nadir angles, the impact of the TRMM boost is mostly mitigated and the change in the precipitation total due to sensitivity degradation is estimated as a decrease of 0.5% (Shimizu et al. 2009). Although the impact of the TRMM boost has been evaluated in previous studies, the change attributable to the switching to redundant electronics has yet to be evaluated. These jumps in quality cause artificial errors and affect the verification of long-term changes in natural variabilities. The stability of sensor calibration is another factor that explains the variations in PR data quality. The absolute calibration of the PR is evaluated by external calibrations (Kozu et al. 2001; Takahashi et al. 2003), and the stability between the PR and a radar calibrator over four years has been determined to be about ±0.5 dB (Takahashi et al. 2003). Takahashi et al. (2003) discussed the long-term stability of the PR via the normalized radar cross section (NRCS, $\sigma^0$) over the oceans and found that the $\sigma^0$ fluctuation is less than 0.1 dB over a monthly time scale. Small drifts in sensor calibration further cause the unnatural variability of the radar reflectivity factor $Z$ affecting the precipitation estimate. Adjustments or corrections of the PR data over the entire period are required to enable a utilization of the data for climate research.

In the current study, we focus on the discontinuity arising from the switching to redundant electronics in June 2009. The PR experienced a major anomaly on 29 May 2009, resulting in a data loss. The Japan Aerospace Exploration Agency (JAXA) and the National Aeronautics and Space Administration (NASA) inferred that the frequency converter intermediate frequency (FCIF)/system control data processing (SCDP) units were not working normally and switched these units from the original A side or FCIF-A/SCDP-A to the redundant B side or FCIF-B/SCDP-B (TRMM Precipitation Radar Team 2011). The B-side observations began on 19 June 2009 and continued until the end of the TRMM mission on 1 April 2015. This event (the “A-to-B event”) caused a change in the level-0 PR count value data, so the calibration coefficients of the B-side PR were somewhat different from those of the A-side PR. Differences in the characteristics of the FCIF-B/SCDP-B and/or their calibrations resulted in a noise power jump in the PR version 7 (V7) product. Figure 1 shows a monthly time series of the PR’s noise power obtained by an average at near-nadir (NN; 21st–29th) angle bins during the post-TRMM-boost period from September 2001 to July 2014 over the TRMM coverage area (35°S–35°N) of the oceans. The noise power is derived from the level-1 PR power data (1B21) V7 product. The background noise from the ocean surface is lower than that over land, so the temporal change of the system noise power that originated from the PR instrument appears in the noise power over the oceans more clearly than over land. The noise power obtained after the TRMM boost gradually increases during the A-side period and slightly decreases 2 months before the anomaly of the A-side PR. After the switching...
from the A side to the B side, the noise power drastically decreases compared with the A side period, and it changes stably during the B-side period. The change in noise power causes the difference in the signal-to-noise ratio (SNR) between the A and B sides, such that the B-side PR is expected to be more sensitive to light precipitation than the A-side PR. Therefore, the impact of the A-to-B event on precipitation estimates should be evaluated.

To use the PR data for climate studies, the quality of the PR data should remain stable over the 17-yr observation period. In this paper, the effect of the A-to-B event is evaluated by generating simulation data. The method of adjustment and data used are introduced in section 2. The results are presented in section 3 and discussed in section 4. Finally, a summary is presented in section 5.

2. Method and data

a. Noise power adjustment

Discontinuity of the noise power causes a sensitivity change in the PR. In the current study, the B-side PR data are adjusted to simulate data with the characteristics of the A-side PR. Since the noise power of the B-side PR is lower than that of the A-side PR, as seen in Fig. 1, noise power $P_n$ and received power $P_r$ of the B-side PR are artificially increased to match those of the A-side PR. Then, the simulated noise power $P'_n$ is produced by adding the additional noise power $A_n$ as

$$ P'_n = P_n + A_n, \quad (1) $$

In the current study, $A_n$ is estimated as the difference in noise power between the A and B sides obtained by the 1B21 product. Table 1 shows the yearly averages of the $P_n$ on the A side in 2008 and on the B side in 2010. Term $A_n$ is obtained as $0.921 \times 10^{-12}$ mW or $-120.35$ dBm. The simulated received power $P'_r$ is also estimated as

$$ P'_r = P_s + P'_n = P_r + A_n, \quad (2) $$

where $P_s$ is the signal power within the radar scattering volume. The current adjustment increases the noise power only and maintains the original signal power. Changes in the angle-bin bias of the noise power and range-bin bias of the received power are described in the appendix, and small bias corrections are applied. The adjustment in (1) and (2) is applied to the 1B21 V7 product. This increase in noise power is expected to slightly degrade the detection of light precipitation. The 1B21 algorithm contains a judgment of precipitation signals (Kumagai et al. 1996). The threshold of precipitation detection is obtained as follows. Kumagai et al. (1996) describes the standard deviation of the power $\sigma$, that is,

$$ \sigma = \frac{\pi P_n}{\sqrt{6}} \left( \frac{1}{N_r} + \frac{1}{N_n} \right), \quad (3) $$

where $N_r$ and $N_n$ are independent sample numbers of $P_r$ and $P_n$, respectively. In the PR algorithm, the rain/no-rain discrimination is defined as

$$ P_r > P_n + m\sigma = P_n \left( 1 + \frac{m\pi}{\sqrt{6}} \left( \frac{1}{N_r} + \frac{1}{N_n} \right) \right). \quad (4) $$

The PR algorithm provides two types of precipitation reliability: “rain possible” ($m = 1$) and “rain certain”

### Table 1. Average of noise power on the A side in 2008 and on the B side 2010 over the TRMM coverage area of the oceans. Data used are taken at NN angle bins.

|                | $10^{-12}$ mW | dBm  |
|----------------|---------------|------|
| A side in 2008 | 7.297         | $-111.37$ |
| B side in 2010 | 6.376         | $-111.95$ |
| Diff (A side minus B side) | 0.921 | $-120.35$ |
In the rain certain case of the PR (m = 3, N_r = 64, and N_n = 256), (4) is determined in decibel scale,

\[ \text{dB}(P_r) - \text{dB}(P_n) > 1.87, \]

where \( \text{dB}(\cdots) = 10 \log(\cdots) \). An impact of the noise increase on precipitation detection is explained as follows. The SNR is defined as SNR = \( P_r/P_n \) and the simulated SNR or SNR' is defined as

\[ \text{SNR}' = \frac{P_r - P_n}{P_n} = \frac{P_r}{P_n} \text{ SNR}. \]

Since \( P_n/P_n' \) is obtained as −0.58 dB as shown in Table 1, the SNR' is 0.58 dB lower than the original. Figure 2 shows changes of the original and simulated SNRs as a function of \( P_r \) in decibel scale. From (5), the original judgment detects a signal when \( P_r \) is higher than −110.09 dBm or when the SNR is higher than −2.68 dB. On the other hand, the simulated judgment requires that \( P_r \) is 0.23 dB higher than original \( P_r \) when the SNR is equal to −2.68 dB. Therefore, the artificial degradation of SNR is the same as the threshold adjustment of the precipitation judgment, that is,

\[ \text{dB}(P_r) - \text{dB}(P_n) > 1.87 + 0.23 = 2.10, \]

if the original \( P_r \) and \( P_n \) are used instead of the noise adjustment. In the current study, the precipitation judgment is indeed adopted in (5) using \( P_n' \) and \( P_r' \).

b. Data used

The level-2 rainfall (2A25) product (Iguchi et al. 2000, 2009) is produced from the 1B21 product via the products of level-1 radar reflectivity (1C21), level-2 surface cross section (2A21), and rain characteristics (2A23). In this simulation study, the noise adjustment and resultant precipitation judgment are conducted in the 1B21 product, and the other algorithms (1C21/2A21/2A23/2A25) to produce precipitation estimates are not modified at all. The simulated or adjusted data of the PR products are generated for 1.5 years from June 2009 to December 2010 and quantitatively assessed for the A-to-B event.

The TMI hydrometeor profile product (2A12) V7 (Kummerow et al. 2001; Gopalan et al. 2010; Kummerow et al. 2011) is also analyzed to estimate the possible bias of the A-to-B event. The precipitation retrieval algorithms are different between the PR and the TMI, but the a priori database for the precipitation estimate by the TMI in V7 is generated from precipitation profiles observed by the PR estimate and those produced by a cloud-resolving model. The TMI data are used only within the PR’s NN

![Fig. 2. SNR dependence as a function of received power in decibel scale. Shown are the original SNR (solid line) and adjusted SNR (dashed line), the original B-side dB\(P_n\) + 1.87 obtained in (5) corresponding to −110.09 dBm (vertical line) and −2.68 or the SNR where dB\(P_n\) is −110.09 dBm (horizontal dotted line).](image)

(about 45 km wide) swath to reduce sampling biases due to differences in swath width between the PR and the TMI. The analysis period of the comparison between the PR and the TMI is the post-TRMM-boost period from September 2001 to July 2014. The quality of the TMI data during this period is stable.

3. Results

a. Changes in 1B21/1C21 products

The impact of adjustment in the current method is primarily confirmed in the level-1 product. Figure 3 shows a case study of the vertical cross section obtained from the adjusted and original data in the 1B21 product. The original (Fig. 3b) and adjusted (Fig. 3a) data are quite similar but differ in terms of the background noise. The difference between the adjusted and original data is also shown in Fig. 3c. While the background of the \( P_r \) determined from the adjusted data is stronger than that derived from the original data, strong signals of \( P_r \) related to precipitation particles are nearly identical between the adjusted and original data, because the unit in Fig. 3c is in decibel scale and small constant changes in noise power become negligible in relative scale when \( P_r \) is large or precipitation is heavy. Precipitation detection, however, is slightly affected in the case of light precipitation signals. Figure 3d shows the precipitation detected by the rain certain threshold used in the PR algorithm. Strong signals with precipitation are detected by both the original and adjusted data (Fig. 3d), but precipitation flags of the adjusted data disappear mainly around the top of a precipitation system. Since the PR primarily observes light precipitation at the storm top, the small sensitivity

![Fig. 3. Original and adjusted 1B21 precipitation products.](image)
change in the PR due to the noise power change appears as a change in storm top characteristics. Figure 4 shows a frequency histogram of the measured \( Z \) or \( Z_m \) at the storm top \( Z_{m,ST} \) derived from the 1C21 product at the NN angles over the TRMM coverage area of the oceans. The storm top is defined by the highest gate where (5) is satisfied for three consecutive range gates. The left tail of the histogram obtained by the original B-side data in 2010 is located in smaller values than that of the A-side data in 2008. While the minimum detectable \( Z_m \) was reported to range from 16 to 18 dBZ by the instrument design (Kozu et al. 2001) and was suggested as 17 dBZ by ground-based radar (Schumacher and Houze 2000), the \( Z_{m,ST} \) derived from the original data in 2008 (2010) in this study turned out to be slightly higher than 18 (17) dBZ. The minimum detectable \( Z_m \) reported by earlier studies is appropriate to the early operation before the TRMM boost because the TRMM altitude increased from 350 to 402.5 km in August 2001 and the minimum detectable \( Z_m \) was degraded by 1.2 dB (Takahashi and Iguchi 2004). Moreover, the precipitation detection in the current study adopts the reliability of rain certain. The current threshold misses light precipitation signals near the noise level, which also apparently degrades the statistics of the minimum detectable \( Z_m \). The histogram of the adjusted B-side data in 2010 shifts to the A-side data in 2008, and the minimum detectable \( Z_m \) of the adjusted B-side data in 2010 is about 18 dBZ. This change is caused by the SNR degradation because of the increase in noise power and missing light precipitation echoes in comparison with the original B-side data, as seen in Fig. 3d. In Fig. 4, the right side of the histogram shows tails corresponding to a large \( Z_{m,ST} \). To minimize the influence of large values that are unreliable, the median is used instead of the average. The difference in the median of \( Z_{m,ST} \) between the A and B sides is 0.75 dB before the B-side adjustment and 0.27 dB after the adjustment. The current adjustment reduces the bias from 0.75 to 0.27 dB. The origin of the remaining 0.27 dB bias in the adjusted data will be discussed in section 4b. The results above show that the sensitivity of the adjusted B-side PR appears to be similar to that of the A-side PR.
b. Changes in 2A23 products

From section 3a the difference in level-1 data between the A and B sides is mitigated by creating the simulation data. The difference in level-2 data between these sides is described in this subsection. The differences in precipitation parameters among the A side, the original B side, and the adjusted B side are listed in Table 2. Figure 5a shows a time series of the storm height detected by the PR. The discontinuity of the storm height derived from the original 2A23 product (Awaka et al. 1997, 2009) is clearly seen after the switching to the B side and its difference between A side in 2008 and B side in 2010 (B side minus A side) is 137.7 m. This discontinuity suggests that the sensitivity change caused by the noise power change results in a quality change of the PR’s storm height statistics. The adjusted data decrease the storm height by 103.5 m and mitigate this discontinuity from 137.7 to 34.2 m (see storm height in Table 2). Figure 5b shows a time series of the precipitation fraction. The precipitation fraction determined from the original B-side data is somewhat higher than that obtained from the A-side data. On the other hand, the precipitation fraction of the adjusted B-side data is close to the original A-side data. The difference in precipitation fraction between the A side and the original B side is found to be 0.112%, and the adjusted B-side data decrease by 0.209% from the original B side [see total precipitation fraction (PF) in Table 2]. The adjusted B side is 0.097% lower than the A side, which may be caused by some natural interannual variabilities. These results suggest that the SNR of the adjusted B-side PR is close to that of the A-side PR, as seen in Fig. 4, and that the difference in noise power is a major factor contributing to the discontinuity of the A-to-B event. The PR 2A23 product also provides the rain type classification so that the change of the precipitation type is also examined and shown in Figs. 5c and 5d. A time series of the stratiform precipitation fraction is similar to the precipitation fraction in Fig. 5b, because stratiform precipitation is dominant over tropical regions (Schumacher and Houze 2003). The jump in the stratiform precipitation fraction derived from the original data in the A-to-B event is mitigated by the use of the adjusted data. The stratiform precipitation fraction of the adjusted B-side data decreases by 0.134% against the original B side and by 0.050% from the A side, while the original B-side data are 0.084% higher than the A-side data (see stratiform PF in Table 2). On the other hand, the convective precipitation fraction decreases by 0.054% with the adjustment, while the original A and B sides differ by only 0.003% (see convective PF in Table 2). In the 2A23 algorithm, convective precipitation is categorized by the threshold of decibels of reflectivity so that a calibration error of absolute value may be linked to a residual jump in the convective precipitation fraction. The regional change of adjustment is mapped in Fig. 6. Averages using all (from 1st to 49th) angle bins in 2010 are determined for the precipitation fraction (Fig. 6a) and the

![Fig. 4](image_url)

**Fig. 4.** Frequency histogram of \( Z_m \) at the storm top detected by the TRMM PR at the NN angles over the TRMM coverage area of the oceans. Bin size is 0.25 dBZ. A side in 2008 (green), original B side in 2010 (red), and adjusted B side in 2010 (blue).

**Table 2.** Differences among the A side (\( A \)), the original B side (\( B_{org} \)), and the adjusted B side (\( B_{adj} \)). Data of the A side in 2008 and the B side in 2010 are analyzed over the TRMM coverage area and subtracted by the monthly climatology calculated from 2002 to 2008. Symbol \( \pm \) shows one standard deviation of the monthly average. In the case of the difference between the A side and the B side, the square root of the sum of squares of these standard deviations is indicated in parentheses.

| Parameter                        | \( B_{adj} - B_{org} \) | \( B_{org} - A \) | \( B_{adj} - A \) |
|----------------------------------|-------------------------|--------------------|--------------------|
| Storm height (m)                 | -103.5 ± 3.7            | 137.7 (± 51.6)     | 34.2 (± 51.5)      |
| Total PF (10^{-2} %)             | -20.86 ± 0.89           | 11.21 (± 12.33)    | -9.64 (± 11.93)    |
| Stratiform PF (10^{-2} %)        | -13.41 ± 0.74           | 8.37 (± 11.79)     | -5.08 (± 11.35)    |
| Convective PF (10^{-2} %)        | -5.44 ± 0.29            | 0.34 (± 2.85)      | -5.10 (± 2.71)     |
| Unconditional \( R \) (10^{-2} mm day^{-1}) | -2.26 ± 0.07         | -5.66 (± 7.97)     | -7.93 (± 7.94)     |
| Unconditional stratiform \( R \) (10^{-2} mm day^{-1}) | -1.06 ± 0.05         | -0.24 (± 4.99)     | -1.30 (± 4.98)     |
| Unconditional convective \( R \) (10^{-2} mm day^{-1}) | -1.12 ± 0.05         | -5.47 (± 4.47)     | -6.59 (± 4.47)     |
storm top height (Fig. 6b). The difference ratio of the precipitation fraction between the adjusted data and the original data (Fig. 6c) is inversely proportional to the average of the precipitation fraction (Fig. 6a), which reveals that the adjustment exerts large impacts on light precipitation areas located off the shores of Peru; California; Benguela, Angola; and the Sahara Desert. This impact is also shown in relative difference of storm heights (Fig. 6d). The relative difference in storm height is similar to the precipitation fraction, and a large change is located in regions with less frequent precipitation. These results demonstrate that degradation of the SNR particularly affects areas with regions of less frequent precipitation.

c. Changes in 2A25 products

In this subsection the change in precipitation estimate is evaluated by comparing the estimates between the adjusted and the original B sides. Figure 7a shows a time series of unconditional mean for surface precipitation $R_s$ derived from the 2A25 product over the TRMM coverage area. The unconditional $R_s$ of the original B side is 0.0566 mm day$^{-1}$ lower than the A side, and the adjusted B-side data decrease by 0.0226 mm day$^{-1}$ against the original B side (see unconditional $R_s$ in Table 2). Although the adjusted B-side data are 0.0793 mm day$^{-1}$ lower than the A side, the systematic difference between the A and B sides can be caused by the interannual variability of precipitation related to ENSO. The unconditional $R_s$ of the stratiform (Fig. 7b) and convective (Fig. 7c) precipitation fraction are also shown. Unconditional stratiform (convective) $R_s$ of the original B side is 0.0024 (0.0547) mm day$^{-1}$ lower than the A side, and the B-side data decrease by 0.0106 (0.0112) mm day$^{-1}$ by the simulation of noise adjustment. The adjusted B-side data of stratiform (convective) $R_s$ are 0.0130 (0.0659) mm day$^{-1}$ lower than the A side, as seen in Table 2. Although the discontinuity of the adjusted data for the convective precipitation fraction is seen in Fig. 5d, the reduction of light precipitation appears to contribute minimally to the precipitation amount. The change in $R_s$ with the adjusted data is further confirmed. Figure 8 shows reverse cumulative histograms of the precipitation fraction and volume sorted as dBR$R_s$. Histograms for convective, stratiform, and total precipitation are also shown individually. The cumulative histograms of the total precipitation fraction (Fig. 8a) between the original and adjusted data depart from each other for light precipitation lower than 0 dB$R$ (1 mm h$^{-1}$). This characteristic is common to stratiform and convective types. A reduction of total precipitation fraction is 0.16% and divided into 0.11% for stratiform
and 0.05% for convective types (Fig. 8c). The absolute change in the precipitation fraction is \(-0.11\%\), but the relative change obtained is about \(-4.6\%\). By comparison, the cumulative difference in precipitation volume (Fig. 8b) is small when compared against the precipitation fraction because light precipitation contributes minimally to the precipitation volume. A decrease in total precipitation volume (Fig. 8d) is \(2.5 \times 10^{-2}\) mm day\(^{-1}\) or \(0.98\%\). The difference in total volume ranges from \(-5\) dBZ \((-0.2\) mm h\(^{-1}\)) to \(15\) dBZ \((-30\) mm h\(^{-1}\)). The dependence of the difference in precipitation volume differs between convective and stratiform types. While the difference in convective type shows a broad range from \(-5\) to \(15\) dBZ, the difference in the stratiform type is lower than \(0\) dBZ. The dependence of difference in precipitation types is attributed to the initial value of the drop size distributions between the convective and stratiform types in the PR algorithm, which changes the relationship between \(Z\) and rain \(R\) (\(Z-R\) relation) for the same \(Z\) value. While the reduction of the stratiform precipitation fraction is 3 times more than that of convective precipitation, conditional precipitation of the convective type is higher than that of the stratiform type, so the resultant difference in precipitation volume for the stratiform and convective types is almost the same.

Regional changes in precipitation estimate attributable to the adjustment are shown in the TRMM coverage map in Fig. 9. In Fig. 9, all angle bins (from 1st to 49th) are used to reduce sampling errors. The angle-bin dependence of the adjusted data is relatively steady in comparison with the dependence of the original data (not shown). The regional distribution of the unconditional \(R_s\) (Fig. 9b) is mostly proportional to the regional average of the fraction (Fig. 9a), similar to that in Fig. 6a. The relative changes of the \(R_s\) fraction (Fig. 9c) and the unconditional \(R_s\) (Fig. 9d) are similar to that of the precipitation fraction (Fig. 6c). Large impacts on the \(R_s\) fraction and the unconditional \(R_s\) are found in regions with less frequent precipitation. The resultant precipitation estimate, as seen in Figs. 7–9d, depends not only on the precipitation fraction but also on the changes in the path-integrated attenuation, the precipitation type, nonuniform beamfilling, and so on, via the reduction in light precipitation. An overall \(R_s\) reduction of the current adjustment is explained by the reduction in light precipitation.

Table 3 summarizes the averages of the precipitation parameters for the original and adjusted B sides and their relative biases. Although the relative bias of the unconditional \(R_s\) is \(-0.90\%\), those of storm height (\(-2.17\%\)) and precipitation fraction (\(-5.15\%\) to \(-4.74\%\)) are not small. These impacts are larger in light precipitation regions than in other regions. The monthly variability of the relative bias is relatively small against the average, which indicates that the impact of the noise adjustment on the precipitation estimates is almost constant on the monthly time scale.

4. Discussion

a. Bias estimate from TMI

From the results given above, the resultant \(R_s\) change attributable to the A-to-B event in June 2009 is estimated as an increase of 0.90%. In this section, the
possible bias of the B-side PR data is also evaluated by independent TMI precipitation data. The quality of the PR data changes because of the A-to-B event, but the TMI data quality remains steady after the TRMM boost. A possible bias of the A-to-B event is estimated by means of the TMI data. The systematic differences in \( R_s \) between PR and TMI during the A-side and B-side periods are individually obtained as

\[
\Delta R_{s,A} = R_{s,TMI}(t_A) - R_{s,PR}(t_A),
\]

(8)

\[
\Delta R_{s,B} = R_{s,TMI}(t_B) - R_{s,PR}(t_B),
\]

(9)

**FIG. 7.** As in Fig. 5, but for (a) unconditional total \( R_s \), (b) stratiform \( R_s \), and (c) convective \( R_s \) (all in mm day\(^{-1}\)).
where $t_A$ and $t_B$ are the periods of the A and B sides, respectively. Since $\Delta R_{Rs, A}$, contains the bias attributed to the A-to-B event $\Delta R_{Rs, AtoB}$ and the systematic difference between PR and TMI before the A-to-B event corresponding to $\Delta R_{Rs, A}$, the bias of PR between the A and B sides is estimated by the difference of their differences,

$$\Delta R_{Rs, AtoB} - \Delta R_{Rs, B} - \Delta R_{Rs, A}. \quad (10)$$

Recalling that the difference between the PR and TMI is large in the El Niño/La Niña phases (e.g., Robertson et al. 2003; Wang et al. 2008; Lau and Wu 2011), the systematic bias between PR and TMI is time dependent. In this study, the months of normal conditions in terms

---

**FIG. 8.** Reverse cumulative histograms of (a) the surface PF (%) and (b) its volume (mm day$^{-1}$) over the TRMM coverage area. Data at NN angle bins. Bin size is 1 dB$R$, and the unit of $R_s$ is mm h$^{-1}$. Shown are original (solid) and adjusted (dashed) data. Shown are total (black), convective (red), and stratiform (blue) data. (c) As in (a), but the surface PF difference between the original data and the adjusted data (adjusted minus original). Color as in (a). (d) As in (c), but for precipitation volume difference. 

**FIG. 9.** (a) Map of the PF (%) obtained from the original data using all (from 1st to 49th) angle bins in 2010. (b) As in (a), but for precipitation amount (mm day$^{-1}$). (c) Difference ratio of the original and the adjusted PF data. (d) As in (c), but for precipitation amount.
of the NOAA Oceanic Niño index (ONI) are used in order to avoid the influences of El Niño/La Niña events. Moreover, the algorithm of the precipitation estimate determined by the TMI differs over the oceans (Kummerow et al. 2011) and land (Gopalan et al. 2010) so that biases must be individually estimated over the oceans and land. Table 4 shows the statistical results of the PR and TMI estimates in normal conditions obtained by the ONI. The precipitation estimates of the PR and TMI are determined over the oceans and land. Table 4 shows the variability of the difference between the PR and the TMI in the range from 3.5% to 4.8%. Since the retrieval methods are different between the PR and the TMI, the large variability of the difference inhibits the accurate estimation of the systematic bias between the A- and B-side PRs.

Table 3. Summary of the averages of original (Org) and adjusted (Adj) and the relative biases (%). Original and adjusted B-side data are analyzed over the TRMM coverage area in 2010. Relative bias is defined as (Adj−Org)/Org. Symbol ± shows one standard deviation of the monthly average.

| Parameter                  | Org          | Adj          | Relative bias (%) |
|-----------------------------|--------------|--------------|-------------------|
| Storm height (m)            | 4771 ± 79.6  | 4667 ± 76.7  | −2.17 ± 0.053     |
| Total PF (%)                | 6.048 ± 0.120| 3.840 ± 0.113| −5.15 ± 0.133     |
| Stratiform PF (%)           | 2.834 ± 0.123| 2.706 ± 0.117| −4.74 ± 0.024     |
| Convective PF (%)           | 1.131 ± 0.044| 1.768 ± 0.042| −4.81 ± 0.017     |
| Unconditional R_s (mm day⁻¹) | 2.515 ± 0.0647| 2.492 ± 0.0641| −0.90 ± 0.021     |
| Unconditional stratiform R_s (mm day⁻¹) | 1.203 ± 0.0468| 1.192 ± 0.0465| −0.89 ± 0.025     |
| Unconditional convective R_s (mm day⁻¹) | 1.310 ± 0.0404| 1.299 ± 0.0401| −0.86 ± 0.038     |

Table 4. Statistical results of the PR and TMI estimates on the A side (September 2001–May 2009) and B side (June 2009–July 2014) over the TRMM coverage area. Month indicates the number of normal conditions determined by ONI. Differences in PR and TMI are analyzed over the TRMM coverage area in 2010. Relative bias is defined as (Adj−Org)/Org. Symbol ± shows one standard deviation of the monthly average.

| Period | Month | PR (mm day⁻¹) | TMI (mm day⁻¹) | PR−TMI (mm day⁻¹) | (PR−TMI)/PRb (%) |
|--------|-------|---------------|---------------|-------------------|------------------|
| Ocean  | A side| 2.78 ± 0.098  | 2.84 ± 0.150  | −0.0581 ± 0.098  | −2.05 ± 3.47     |
|        | B side| 2.83 ± 0.094  | 2.84 ± 0.130  | −0.0133 ± 0.098  | −0.47 ± 3.64     |
|        | B − A | 0.0497 (± 0.136) | 0.0047 (± 0.199) | 0.0448 (± 0.142) | 1.58 (± 5.03)    |
| Land   | A side| 2.84 ± 0.199  | 2.60 ± 0.206  | 0.241 ± 0.141    | 8.23 ± 4.82      |
|        | B side| 2.93 ± 0.137  | 2.65 ± 0.174  | 0.278 ± 0.127    | 9.48 ± 4.35      |
|        | B − A | 0.0901 (± 0.241) | 0.0538 (± 0.270) | 0.0363 (± 0.190) | 1.24 (± 6.49)    |
| Globe  | A side| 2.80 ± 0.080  | 2.75 ± 0.088  | 0.0475 ± 0.087   | 1.66 ± 3.05      |
|        | B side| 2.86 ± 0.062  | 2.77 ± 0.084  | 0.0893 ± 0.074   | 3.12 ± 2.59      |
|        | B − A | 0.0639 (± 0.101) | 0.0221 (± 0.121) | 0.0418 (± 0.114) | 1.46 (± 4.00)    |

b. Uncertainty of the current simulation and other factors

The noise power adjustment successfully mitigates small differences in the sensitivity of the PR between the A and B sides. The original sensitivity difference between the original A and B sides obtained as 0.75 dB for Z_m,ST as seen in Fig. 4 is reduced substantially, but the sensitivity difference of 0.27 dB between the A and adjusted B sides remains. This difference arises from the uncertainty of the current simulation and/or the potential error of calibration. The uncertainty of the simulation is evaluated via the
change in the simulation during the A-side period. The noise power of the A side dropped slightly about 2 months before the anomaly. Here, the change in the noise power during the A side is adjusted to be $-111.37 \text{ dBm}$ by the simulation. Figure 10 shows daily time series of the noise power (dashed) and $Z_{m,ST}$ (solid) obtained from February 2009 to August 2009. Two parameters of the original data, denoted by the gray lines, show changes in the same phase. The noise power dropped at the end of March from $-111.40$ to $-111.55 \text{ dBm}$ and a change of $0.29 \times 10^{-13} \text{ mW}$ or $-125.31 \text{ dBm}$ is observed. At the end of March, $Z_{m,ST}$ also decreased from 20.2 to 20.0 dBZ. The noise power change at the end of March in 2009 can be assumed to cause an SNR change in the A-side PR and simulate the noise power adjustment described in section 2. The original A-side data from April 2009 to May 2009 were acquired to simulate the adjustment of noise power. The continuity of both the noise power and the median of $Z_{m,ST}$ between the original A side from February to March and the adjusted A side from April to May, as indicated by black lines in Fig. 10, is simulated reasonably. By comparison, the $Z_{m,ST}$ of the adjusted B-side data is about 0.3 dB lower than that of the A-side period, which means the residual difference between the A side and the simulated B side may arise from an error in the adjustment method rather than an error in the calibration factor between these sides.

The difference in noise power between the A and B sides in V7 is obtained as 0.58 dB. This difference is caused by sensitivity changes attributable to the degradation of the A side over time and the calibration change of the PR. The system noise that originated from the A and B sides is identical to those determined from a prelaunch test. After the TRMM launch and the switching of the internal attenuator of the PR from 6 to 9 dB on February 1998, the digital number of the A-side noise power derived from the level-0 data increased by about 0.8 count at the end of the A-side observation (not shown). This count change corresponds to a change in noise power of about 0.30 dB, and the residual difference may be caused by calibration errors. The small calibration change during the A-side period is a source of residual error of the current adjustment between the A and B sides.

The difference in the calibration curves between the A and B sides could cause an error for continuity of the PR data. The A-to-B event switched the FCIF/SCDP system, including the analog-to-digital conversion, and changed the calibration curves slightly. Although the change in the slope of the calibration curves is taken into account by using the internal calibration data (Kozu et al. 2001), uncertainty of the calibration curves between the A and B sides may partially explain the residual error.

5. Summary

Precipitation observations by the TRMM PR were conducted for more than 17 years. Homogeneity of long-term PR data quality is essential to study changes in water and energy cycle related to interannual and decadal variabilities. In this study, we aim to develop precipitation climate record from the 17-yr PR data. The PR data show a discontinuity in
quality associated with the switching to redundant electronics (A-to-B event) in June 2009. In version 7 of the level-1 PR product, a difference in noise power between before and after the A-to-B event is found so that a change in signal-to-noise ratio is expected. In this work, the noise power and the received power of the B-side PR after the A-to-B event are artificially increased to match those of the A-side PR to remove the effect of the signal-to-noise change. An obvious discontinuity of the storm height caused by the A-to-B event is mitigated with the adjusted data. Differences in other precipitation characteristics are also mitigated overall. The precipitation derived from the adjusted data over the TRMM coverage area decreased by 0.90% compared with that determined from the original data. This decrease is caused by the reduction of light precipitation. The effect of the A-to-B event on the precipitation amount for the PR estimate is examined to compare the A and B sides using the TMI estimate, which shows that the precipitation amount of the B-side PR is 1.24%–1.58% higher than that of the A side. Although some residual error remains as a calibration issue, the results of the adjustment indicate achievements mitigating discontinuities attributed to the A-to-B event.

The current study reveals that slight changes in the detectability of light precipitation associated not only with the TRMM boost but also with the A-to-B event should be considered to develop a precipitation climate record observed by the PR. It is true that the noise power appears to increase almost linearly from 2002 to 2008 during the A-side operation as seen in Fig. 1. This issue is closely related to the calibration of the A side. Although some residual error remains as a calibration issue, the results of the adjustment indicate achievements mitigating discontinuities attributed to the A-to-B event.

The next step is to explore the long-term stability of the PR’s calibration and the effect of factors such as the TRMM boost and the power. Adjustments of the PR data by taking into account all factors, such as the TRMM boost and the power, should be considered to develop a precipitation climate record observed by the PR. This is because the noise power appears to increase almost linearly from 2002 to 2008 during the A-side operation as seen in Fig. 1. Furthermore, changes in the angle-bin dependence of $P_r$ and the range-bin dependence of $P_n$ are found from the statistical analysis. The PR switches on and off the power to the transmitter and receiver systems to save electric power consumption, causing a small transient change in gain as a function of the range-bin number $r$. The noise sampling window by the PR is different depending on the angle-bin number (Takahashi and Iguchi 2008), and the bias of $P_r$ is a function of the angle-bin number $i$. In the IB21 algorithm, biases are removed by the offset table,

$$\text{dB}P_r(r) = \text{dB}P_{r,0}(r) - B_r(r), \quad \text{and}$$

$$\text{dB}P_n(i) = \text{dB}P_{n,0}(i) - B_n(i),$$

where $P_{r,0}$ and $P_{n,0}$ are the uncorrected $P_r$ and $P_n$, respectively; and $B_r$ and $B_n$ are the biases of $P_r$ and $P_n$, respectively. In this study, the average of the $P_n$ at NN angle bins, which range from the 21st to the 29th angle bin, $P_{n,NN}$ is considered as the standard, and the range-bin bias of $P_r$, $\Delta P_r$, and the angle-bin bias of $P_n$, $\Delta P_n$, are expressed as

$$\Delta P_r(r, t) = P_r(r, t) - P_{n,NN}$$

and

$$\Delta P_n(i, t) = P_n(i, t) - P_{n,NN},$$

where $t$ is the offset change of the B-side data is estimated from the difference of their difference between the A side in 2008 and the B side in 2010,

$$\Delta B_r(r) = \Delta P_r(r, 2010) - \Delta P_r(r, 2008),$$

and

$$\Delta B_n(i) = \Delta P_n(i, 2010) - \Delta P_n(i, 2008),$$

where $\Delta B_r$ and $\Delta B_n$ are the B-side changes of the offsets of $P_r$ and $P_n$, respectively. The PR level-1 product contains $P_i$ data for different range-bin numbers by each

**Acknowledgments.** The TRMM PR and TMI version 7 products were provided by the Japan Aerospace Exploration Agency (JAXA). Oceanic Niño index data are available online (at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml).

The work was supported by the Japan Aerospace Exploration Agency (JAXA) as part of authors’ regular job responsibilities. The authors thank Mr. Higashiuwatoko of the Remote Sensing Technology Center of Japan (RESTEC) for generating data. They also thank Mr. Kojima of JAXA, Mr. Hanado of the National Institute of Information and Communications Technology (NICT), Mr. Yoshida of RESTEC, and Mr. Masaki of the JAXA Earth Observation Research Center (EORC) for providing valuable information and comments. The authors thank the anonymous reviewers for providing positive comments, which helped to improve this paper.

**APPENDIX**

**Range-Bin Dependence of the Received Power and Its Correction for the B Side**

According to the level-1 PR product, the $P_n$ of the backup B side is lower than that of the original A side, as seen in Fig. 1. Furthermore, changes in the angle-bin dependence of $P_n$ and the range-bin dependence of $P_r$ are found from the statistical analysis. The PR switches on and off the power to the transmitter and receiver systems to save electric power consumption, causing a small transient change in gain as a function of the range-bin number $r$. The noise sampling window by the PR is different depending on the angle-bin number (Takahashi and Iguchi 2008), and the bias of $P_r$ is a function of the angle-bin number $i$. In the IB21 algorithm, biases are removed by the offset table,
angle-bin number so that $\Delta B$, obtained at each angle-bin number is sorted as a function of range-bin number. Figure A1a shows $B$, and indicates that a bias from 0.03 to 0.08 dB is found for a small $r$ ranging from 0 to 30. This offset change mirrors $B_n$ (Fig. A1b). The noise sampling window in angle bins 15–35 is located at a large $r$ (about 400 range-bin number), where the effect of transient phenomena is minimal, so that the bias is ignored. By contrast, the noise sampling windows in the off-nadir angle bins 1–14 and 36–49 are located at a small $r$, thus causing a systematic dependence of $B_r$. These offset changes are adopted to create the adjusted B-side data.

Fig. A1. Estimated B-side offset changes of dependence for (a) the range-bin number of $P_r$ and (b) the angle-bin number of $P_n$. Symbols are obtained from the differences between the A side in 2008 and the B side in 2010. B-side offset used to create the B-side adjusted data (solid line).
REFERENCES

Adler, R. F., and Coauthors, 2003: The Version-2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present). J. Hydrometeor., 4, 1147–1167, doi:10.1175/1525-7541(2003)004<1147:TVGPCP>2.0.CO;2.

Awaka, J., T. Iguchi, H. Kumagai, and K. Okamoto, 1997: Rain type classification algorithm for TRMM precipitation radar. IGARSS ’97: International Geoscience and Remote Sensing Symposium; Remote Sensing—A Scientific Vision for Sustainable Development, T. I. Stein, Ed., Vol. 4, IEEE, 1635–1635, doi:10.1109/IGARSS.1997.608993.

——, ——, and K. Okamoto, 2009: TRMM PR standard algorithm 2A23 and its performance on bright band detection. J. Meteor. Soc. Japan, 87A, 31–52, doi:10.2151/jmsj.87A.31.

Gopalakrishnan, K., N.-Y. Wang, F. Ferraro, and C. Liu, 2010: Status of the TRMM 2A12 land precipitation algorithm. J. Atmos. Oceanic Technol., 27, 1343–1354, doi:10.1175/2010JTECHA1454.1.

Hirose, M., S. Shimizu, R. Oki, T. Iguchi, D. A. Short, and K. Nakamura, 2012: Incidence-angle dependency of TRMM PR rain estimates. J. Atmos. Oceanic Technol., 29, 192–206, doi:10.1175/JTECH-D-10-00087.1.

Hou, A. Y., and Coauthors, 2014: The Global Precipitation Measurement Mission. Bull. Amer. Meteor. Soc., 95, 701–722, doi:10.1175/BAMS-D-13-00164.1.

Iguchi, T., T. Kozu, R. Meneghini, J. Awaka, and K. Okamoto, 2000: Rain-profiling algorithm for the TRMM precipitation radar. J. Appl. Meteor., 39, 2038–2052, doi:10.1175/1520-0450(2000)039<2038:RAPTR>2.0.CO;2.

——, ——, J. Kwiatkowski, R. Meneghini, J. Awaka, and K. Okamoto, 2009: Uncertainties in the rain profiling algorithm for the TRMM Precipitation Radar. J. Meteor. Soc. Japan, 87A, 1–30, doi:10.2151/jmsj.87A.1.

Ikai, J., and K. Nakamura, 2003: Comparison of rain rates over the ocean derived from TRMM Microwave Imager and precipitation radar. J. Atmos. Oceanic Technol., 20, 1709–1726, doi:10.1175/1520-0442(2003)020<1709:COROT>2.0.CO;2.

Kozu, T., and Coauthors, 2001: Development of precipitation radar onboard the Tropical Rainfall Measuring Mission (TRMM) satellite. IEEE Trans. Geosci. Remote Sens., 39, 102–116, doi:10.1109/36.898669.

Kumagai, H., K. Toshiaki, and T. Iguchi, 1996: Development of an algorithm for rain/no-rain discrimination (in Japanese). Rev. Commun. Res. Lab, 42, 317–323.

Kummerow, C. D., and Coauthors, 2000: The status of the Tropical Rainfall Measuring Mission (TRMM) after two years in orbit. J. Appl. Meteor., 39, 1965–1982, doi:10.1175/1520-0450(2000)039<1965:TSOTTR>2.0.CO;2.

——, and Coauthors, 2001: The evolution of the Goddard Profiling Algorithm (GPROF) for rainfall estimation from passive microwave sensors. J. Appl. Meteor., 40, 1801–1820, doi:10.1175/1520-0450(2001)040<1801:TEOTGP>2.0.CO;2.

——, S. Ringerud, J. Crook, D. Randel, and W. Berg, 2011: An observationally generated a priori database for microwave rainfall retrievals. J. Atmos. Oceanic Technol., 28, 113–130, doi:10.1175/2010JTECHA1468.1.

Lau, K.-M., and H.-T. Wu, 2011: Climatology and changes in tropical oceanic rainfall characteristics inferred from Tropical Rainfall Measuring Mission (TRMM) data (1998–2009). J. Geophys. Res., 116, doi:10.1029/2011JD015827.

Masunaga, H., T. Iguchi, R. Oki, and M. Kachi, 2002: Comparison of rainfall products derived from TRMM Microwave Imager and precipitation radar. J. Appl. Meteor., 41, 849–862, doi:10.1175/1520-0450(2002)041<0849:COPDTR>2.0.CO;2.

Robertson, F. R., D. E. Fitzjarrald, and C. D. Kummerow, 2003: Effects of uncertainty in TRMM precipitation radar path integrated attenuation on interannual variations of tropical oceanic rainfall. Geophys. Res. Lett., 30, 1180, doi:10.1029/2002GL016416.

Schumacher, C., and R. A. Houze, 2000: Comparison of radar data from the TRMM satellite and Kwajalein oceanic validation site. J. Appl. Meteor., 39, 2151–2164, doi:10.1175/1520-0450(2000)040<2151:COROTP>2.0.CO;2.

Shige, S., H. Sasaki, K. Okamoto, and T. Iguchi, 2006: Validation of rainfall estimates from the TRMM precipitation radar and microwave imager using a radiative transfer model: 1. Comparison of the version-5 and -6 products. Geophys. Res. Lett., 33, L13803, doi:10.1029/2006GL026350.

Shimizu, S. R. Oki, T. Tagawa, T. Iguchi, and M. Hirose, 2009: Evaluation of the effects of the orbit boost of the TRMM satellite on PR rain estimates. J. Meteor. Soc. Japan, 87A, 83–92, doi:10.2151/jmsj.87A.83.

Takahashi, N., and T. Iguchi, 2004: Estimation and correction of beam mismatch of the Precipitation Radar after an orbit boost of the tropical rainfall measuring mission satellite. IEEE Trans. Geosci. Remote Sens., 42, 2362–2369, doi:10.1109/TGRS.2004.837334.

——, and ——, 2008: Characteristics of TRMM/PR system noise and their application to the rain detection algorithm. IEEE Trans. Geosci. Remote Sens., 46, 1697–1704, doi:10.1109/TGRS.2008.916205.

——, H. Kuroiwa, and T. Kawanishi, 2004: Four-year result of external calibration for Precipitation Radar (PR) of the Tropical Rainfall Measuring Mission (TRMM) satellite. IEEE Trans. Geosci. Remote Sens., 41, 2398–2403, doi:10.1109/TGRS.2003.817180.

TRMM Precipitation Radar Team, 2011: Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar algorithm instruction manual for version 7. JAXA and NASA, 170 pp. [Available online at http://www.corc.jaxa.ja/PRM/documents/PR_algorithm_product_information/pr_manual/PR_Instruction_Manual_V7.L1.pdf.

Wang, J.-J., R. F. Adler, and G. Gu, 2008: Tropical rainfall-surface temperature relations using Tropical Rainfall Measuring Mission precipitation data. J. Geophys. Res., 113, D18115, doi:10.1029/2007JD009540.

Wentz, F. J., L. Ricciardulli, K. Hilburn, and C. Mears, 2007: How much more rain will global warming bring? Science, 317, 233–235, doi:10.1126/science.1140746.

Xie, P., and P. A. Arkin, 1997: Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. Bull. Amer. Meteor. Soc., 78, 2539–2558, doi:10.1175/1520-0477(1997)078<2539:GPAYMA>2.0.CO;2.