Correction of Path-Integrated Attenuation Estimates Considering the Soil Moisture Effect for the GPM Dual-Frequency Precipitation Radar

SHINTA SETO,a TOSHIO IGUCHI,b AND ROBERT MENEGHINIC

a Graduate School of Engineering, Nagasaki University, Nagasaki, Japan
b Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland
c NASA Goddard Space Flight Center, Greenbelt, Maryland

(Manuscript received 16 August 2021, in final form 16 February 2022)

ABSTRACT: Spaceborne precipitation radars, including the Tropical Rainfall Measuring Mission’s Precipitation Radar (PR) and the Global Precipitation Measurement Mission’s Dual-Frequency Precipitation Radar (DPR), measure not only precipitation echoes but surface echoes as well, the latter of which are used to estimate the path-integrated attenuation (PIA) in the surface reference technique (SRT). In our previous study based on analyzing PR measurements, we found that attenuation-free surface backscattering cross sections (denoted by \( \sigma_0^s \)) over land increased in the presence of precipitation. This behavior, called the soil moisture effect, causes an underestimate of the PIA by the SRT as the method does not explicitly consider this effect. In this study, measurements made by Ku-band Precipitation Radar (KuPR) and Ka-band Precipitation Radar (KaPR), which comprise the DPR, were analyzed to examine whether KuPR and KaPR exhibit similar dependencies on the soil moisture as does the PR. For both KuPR and KaPR, an increase in \( \sigma_0^s \) was observed for a large portion of the land area, except for forests and deserts. Results from the Hitschfeld–Bordan (HB) method suggest that \( \sigma_0^s \) increases with the surface precipitation rate for light precipitation events. Meanwhile, for heavy precipitation, owing to the degradation of the HB method, it is difficult to estimate \( \sigma_0^s \) quantitatively. Thus, a correction method for PIA that considers the soil moisture effect was developed and implemented into the DPR standard algorithm. With this correction, the surface precipitation rate estimates increased by approximately 18% for KuPR and 15% for the normal scan of KaPR over land.

KEYWORDS: Precipitation; Soil moisture; Radars/Radar observations; Remote sensing; Satellite observations

1. Introduction

a. Background and study purpose

Spaceborne precipitation radars have been operating for more than 20 years (Nakamura 2021), beginning with the Precipitation Radar (PR; Kozu et al. 2001) on the Tropical Rainfall Measuring Mission (TRMM; Kummerow et al. 1998) satellite, which operated from 1997 to 2015, and continuing with the Dual-Frequency Precipitation Radar (DPR; Kojima et al. 2012; Iguchi 2020) on the Global Precipitation Measurement (GPM; Hou et al. 2014; Skofronick-Jackson et al. 2017) mission’s core satellite, which has been in operation since 2014. As spaceborne precipitation radars measure not only precipitation echo but also surface echo, the surface reference technique (SRT; Meneghini et al. 2000, 2004, 2012, 2015, 2021) can be applied to the precipitation retrieval. The SRT is a method for estimating path-integrated attenuation (PIA; its value in decibel is denoted by \( A \)) using the difference between the measured surface backscattering cross sections (values in decibels are denoted by \( \sigma_0^m \)) inside and outside the precipitation area. Unless stated otherwise, all surface backscattering cross sections and path-integrated attenuations in this paper are expressed in decibels.

Seto and Iguchi (2007, hereafter SI07) analyzed the outputs of the PR standard algorithm version 6 (Iguchi et al. 2000; Meneghini et al. 2004) and showed that \( \sigma_0^m \) changes not only because of rain attenuation under rainfall but also because of rainfall-induced changes in the surface conditions. In particular, over land, the actual (attenuation-free) surface backscattering cross sections (denoted by \( \sigma_0^s \)) increase in the presence of rainfall. This behavior is called the soil moisture effect. In general, the increase in the surface soil moisture causes an increase in the dielectric constant; as the dielectric constant is larger for water than that for soil particle, this leads to an increase in \( \sigma_0^s \). Several studies including Oki et al. (2000), Seto et al. (2003), Lee and Anagnostou (2004), and Stephen et al. (2010) revealed the relationship between \( \sigma_0^m \) by PR and surface soil moisture. Tagawa et al. (2004) showed the dependence of \( \sigma_0^m \) on surface soil moisture by an experiment using 35-GHz polarimetric scatterometer. Frappart et al. (2015) showed the relationship between \( \sigma_0^m \) using measurements from Ka-band altimeter (ALtiKa) on board the Satellite for...
Argos and ALtiKa (SARAL) and surface soil moisture. Fatras et al. (2016) conducted an experiment to show the relationship between $\sigma_0^m$ at 34.5 GHz and surface soil moisture.

As the SRT does not explicitly consider changes in surface conditions, it may result in significantly biased PIA estimates. In the PR standard algorithm version 7 (Iguchi et al. 2009; TRMM Precipitation Radar Team 2011), following SI07, an adjustment term of 0.5 dB was added to the PIA estimated by the SRT to account for the soil moisture effect over land. In the DPR standard algorithm version 06 (Meneghini et al. 2021; Seto et al. 2021), no adjustment is given to the PIA estimated by the SRT. Therefore, in this study, the soil moisture effect was analyzed using outputs of the DPR standard algorithm version 06, and a correction method for the PIA estimated using the SRT was developed.

b. Overview of DPR

The DPR consists of a Ku-band Precipitation Radar (KuPR; 13.6 GHz) and a Ka-band Precipitation Radar (KaPR; 35.5 GHz). The microwave frequency of the KuPR is near that of the PR (13.8 GHz), and the scan pattern of the KuPR is the same as that of the PR; both radars scan in the cross-track direction and measure 49 pixels over each scan. An angle bin number $i$ (1–49) is allocated to the pixels, where the incidence angle, measured at the surface, is given approximately by $0.75^\circ \times |25 - i|$. The KaPR has a normal mode and a high-sensitivity mode. It measures 25 pixels per scan in the normal mode. An angle bin number $j$ (1–25) is allocated to the pixels, wherein the incidence angle is $0.75^\circ \times |13 - j|$. The KaPR’s pixel with angle bin number $j$ matches the KuPR’s pixel with an angle bin number $j + 12$. Dual-frequency measurements are available at these pixels. The KaPR measurements in the normal mode are called “KaPR for matched scan” (KaMS) hereafter in this study. In addition, the part of the swath where KaMS measurements are available is called the inner swath, while the rest of the swath is called the outer swath.

After the 25-pixel measurements by the KaMS, 24 pixels are measured using the KaPR in the high-sensitivity mode. These measurements are called “KaPR with high sensitivity” (KaHS). The KaHS measurements are inferior to the KaMS measurements in terms of the vertical resolution (500 m for KaHS and 250 m for KaMS). However, the KaHS is superior to the KaMS in terms of the minimum detection level (13.71 dBZ for KaHS and 19.18 dBZ for KaMS; Masaki et al. 2022). At the beginning of the mission, the KaHS beams were directed along the inner swath over a scan interleaved by two normal scans. An angle bin number $h$ (1–24) is allocated to KaHS pixels, wherein the incidence angle is $0.75^\circ \times |h - 12.5|$. The scan pattern of KaHS was changed in May 2018, but the data taken after the scan pattern change are not used in this study.

c. DPR standard algorithm

The level-2 DPR standard algorithm consists of the KuPR algorithm, the KaPR algorithm, and the dual-frequency algorithm. While the dual-frequency algorithm uses both KuPR and KaPR measurements, only KuPR (KaPR) measurements are available for the KuPR (KaPR) algorithm. Each algorithm is composed of six major modules: Preparation module, Vertical profile module, Classification module, SRT module, Drop size distribution module, and Solver module. As the details of the DPR standard algorithm and its modules are described in Iguchi et al. (2018) and other documents, the following explanation is limited to considerations relevant to this study.

1) SINGLE-FREQUENCY ALGORITHMS

The single-frequency algorithms (KuPR and KaPR algorithms) are explained in this section. In the Preparation module, the presence or absence of precipitation is judged at each pixel. If precipitation is present, the pixel is called a precipitation pixel or P pixel. If there is no precipitation, the pixel is called a no-precipitation pixel or NP pixel. Further, $\sigma_0^m$ is calculated from the surface echo, and the surface type (land, ocean, coast, or in-land water) is determined at each pixel.

In the Vertical profile module, the vertical profiles of cloud liquid water, water vapor, and oxygen are estimated, and the attenuation caused by these constituents (called nonprecipitation attenuation) is calculated. The path-integrated value is denoted by $A_{\text{avg}}$. An environmental grid dataset (spatial resolution of 0.5° latitude × 0.5° longitude and temporal resolution of 6 h) was produced based on the Japan Meteorological Agency’s analysis and forecast data, and was used to estimate the profiles of cloud liquid water, water vapor, and oxygen at NP pixels. Meanwhile, at P pixels, the vertical profiles of water vapor and oxygen are estimated using the environmental grid dataset, and the vertical profile of cloud liquid water is estimated by referencing a database that was produced from the outputs of a global cloud resolving model. More details regarding the Vertical profile module are provided in Kubota et al. (2020a).

In the SRT module, the PIA is estimated at the P pixels. The estimate is denoted by $A_{\text{SRT}}$. NP pixels that have similar surface conditions to the target P pixel are used, and the sample mean and standard deviation of the $\sigma_0^m$ values at the NP pixels are calculated. Over land, several reference methods are applied simultaneously, including the forward along-track reference method (FA), backward along-track reference method (BA), and temporal reference method (TR). In the FA (BA), the sample mean and standard deviation of the $\sigma_0^m$ values from eight NP pixels measured before (after) the target P pixel, at the same angle bin number and surface type as the P pixel, constitute the rain-free reference data. If eight NP pixels are not found within a 50-pixel distance from the target P pixel, the reference method is not used. For the TR, the sample mean and standard deviation of the $\sigma_0^m$ values at NP pixels are calculated in advance over a grid (0.5° latitude × 0.5° longitude) for each season (JJA, SON, DJF, and MAM) and incidence angle (each 0.75° bin). The values at the same grid, season, and incidence angle as the target P pixel are used. $A_{\text{SRT}}$ is given in Eq. (1):

$$A_{\text{SRT}} = \sigma_0^m|X| - \sigma_0^m|P|,$$

where a variable with [X] denotes the value of the weighted average of the NP pixels referenced in SRT and a variable with
[P] denotes the value at the target P pixel. The precise definition of the weighted average is given in the appendix. A detailed description of the SRT module is provided in Meneghini et al. (2021).

In the Solver module, $A_{\text{SRT}}$ is used as an input to retrieve physical variables, such as the precipitation rate. As $A_{\text{SRT}}$ is affected by nonprecipitation attenuation, it must be corrected before the retrieval procedure to provide the PIA caused by precipitation particles only (denoted by $A_p$). The terms appearing on the right-hand side of Eq. (1) are decomposed, as expressed in Eqs. (2) and (3):

$$s_0^m[P] = s_0^p[P] - A_p - A_{np}[P]$$

and

$$s_0^m[X] = s_0^p[X] - A_{np}[X].$$

By substituting Eqs. (2) and (3) into Eq. (1), Eq. (4) can be obtained:

$$A(\text{SRT}) = A_p + A_{np}[P] - A_{np}[X] - \delta s_0^p,$$

where

$$\delta s_0^p \equiv s_0^p[P] - s_0^p[X].$$

From Eq. (4), $A_p$ is given as follows:

$$A_p = A(\text{SRT}) + A_{np}[X] - A_{np}[P] + \delta s_0^p.$$ 

However, in the version 06 algorithm, $\delta s_0^p$ is ignored, so that $A_p$ is estimated by Eq. (7):

$$A_p(\text{SRT}) = A(\text{SRT}) + A_{np}[X] - A_{np}[P].$$

where $A_p$ is renamed as $A_p(SRT)$ to describe the estimation method. The relationship among the variables related to SRT are summarized in Fig. 1a. For each method of SRT (FA, BA, and TR), similar equations are derived as shown in the appendix.

$A_p(SRT)$ is usually different from the final estimate of $A_p$ in the Solver module [denoted by $A_p(\text{SLV})$]. As the reliability of the SRT increases, $A_p(\text{SLV})$ moves closer to $A_p(SRT)$. More details regarding the Solver module are provided in Seto et al. (2021).

In the single-frequency algorithm, the six modules are executed twice. In the first execution, tentative estimates are obtained, and in the second execution, some of the tentative estimates are used to recalculate other variables. For example, cloud liquid water at a P pixel is given as a function of the surface precipitation rate estimates from the first execution. Note that the estimates provided by the second execution are the final estimates.

2) DUAL-FREQUENCY ALGORITHM

The dual-frequency algorithm has the same six modules as the single-frequency algorithms, but there are differences
within each module. In this section, the differences related to this study are briefly explained.

In the SRT module, an estimate of the differential path attenuation, the difference in $A$ between KuPR and KaPR (denoted by $A_k$), is based on the difference in the $s^0_m$ values between KuPR and KaPR (denoted by $\sigma^0_{m,k}$). The method to derive $A_k$ from $\sigma^0_{m,k}$ is the same as that used to derive $A$ from $s^0_m$ in the single-frequency algorithms and is called the dual-frequency surface reference technique (DSRT). In the Solver module, $A_k$ is used as an input to retrieve physical variables after it is corrected for nonprecipitation attenuation.

d. Data preparation

In this study, the outputs of the DPR standard algorithm (version 06A) from 2015 to 2020 were analyzed. Hereafter, unless otherwise specified, the period of analysis is 6 years for KuPR and KaMS, and 3 years (from 2015 to 2017) before the scan pattern change for KaHS. Note that KaHS after the scan pattern change was not processed in version 06A, and thus, it was not analyzed in this study.

In this study, the analysis preparation was as follows. The average $s^0_m$ at NP pixels over land is calculated over a monthly 1° latitude $\times$ 1° longitude grid for each angle bin. The average value is denoted by $\overline{s^0_m}$, so that for an instantaneous value of $s^0_m$, the anomaly from the corresponding $\overline{s^0_m}$ is denoted by $\Delta s^0_m$, as expressed in Eq. (8):

$$\Delta s^0_m = s^0_m - \overline{s^0_m}. \quad (8)$$

The surface backscattering cross section corrected for nonprecipitation attenuation is denoted by $\sigma^0_m$, as expressed in Eq. (9):

$$\sigma^0_m = s^0_m + A_p. \quad (9)$$

A space–time average of $\sigma^0_m$ at NP pixels over land is calculated in an identical manner to that for $s^0_m$ and is denoted by $\overline{\sigma^0_m}$. By taking the average of the both terms in Eq. (9), the following equations are obtained:

$$\overline{\sigma^0_m} = \overline{s^0_m} + \overline{A_p}. \quad (10)$$

where $\overline{A_p}$ is the average $A_p$ at NP pixels over land at each angle bin over the same space–time grid as described above. For an instantaneous value of $\sigma^0_m$, the anomaly from the corresponding $\overline{\sigma^0_m}$ is denoted by $\Delta \sigma^0_m$, as expressed in Eq. (11):

$$\Delta \sigma^0_m = \sigma^0_m - \overline{\sigma^0_m}. \quad (11)$$

Relationship among the variables at an NP pixel is summarized in Fig. 1b.

At a P pixel, Eq. (12) is true:

$$\sigma^0_e = \sigma^0_m + A_p. \quad (12)$$

If $A_p$ is estimated using method M, it is denoted by $A_p(M)$, where M is a generic name to describe the method. For example, $A_p$(SRT) was estimated using Eq. (7). Thus, if $\sigma^0_m$ is calculated with $A_p(M)$, it is denoted by $\sigma^0_e(M)$ as follows:

$$\sigma^0_e(M) = \sigma^0_m + A_p(M). \quad (13)$$

For an instantaneous value of $\sigma^0_e(M)$, the anomaly from the corresponding $\overline{\sigma^0_e(M)}$ is denoted by $\Delta \sigma^0_e(M)$, as expressed in Eq. (14):

$$\Delta \sigma^0_e(M) = \sigma^0_e(M) - \overline{\sigma^0_e(M)}. \quad (14)$$

The relationship among the variables at a P pixel is summarized in Figs. 1c and 1d. $\Delta \sigma^0_e$ indicates the soil moisture effect; if a soil moisture effect exists, $\Delta \sigma^0_e$ is positive. In the case of light precipitation (Fig. 1c), where $A_p$ is not large, $\Delta \sigma^0_e$ and $\Delta \sigma^0_m$ may be positive. In the case of heavy precipitation (Fig. 1d), where $A_p$ is large, $\Delta \sigma^0_e$ and $\Delta \sigma^0_m$ are negative.

e. Composition of this study

Based on the preparatory comments and definitions provided, the purpose of this study is to estimate the value of $\Delta \sigma^0_m$ to correct the $A_p$(SRT) to $A_p$ (as illustrated in Fig. 1a). The remainder of this paper is organized as follows.

In section 2, $\Delta \sigma^0_m$ and $\Delta \sigma^0_e$ at NP pixels (as illustrated in Fig. 1b), either located near a P pixel or measured soon after a precipitation event, are analyzed. These NP pixels are expected to have a relatively higher surface soil moisture than other NP pixels and to exhibit a soil moisture effect. Note that the analysis of the NP pixels is free from the estimation error of $A_p$. In section 3, the estimates of $\Delta \sigma^0_e$ at NP pixels (as illustrated in Figs. 1c,d) are analyzed for different precipitation rate categories. In section 4, an estimation method for $\Delta \sigma^0_e$ is developed and implemented in the single-frequency algorithms. Further, the effect of the correction of $A_p$(SRT) on the precipitation rate estimates is examined. Finally, a summary is provided in section 5.

2. Analysis of the soil moisture effect at NP pixels

a. NP pixels adjacent to a P pixel

1) PR (review)

In SI07, using data from the PR, the behavior of $\Delta \sigma^0_m$ at the NP pixels adjacent to a P pixel was analyzed. NP pixels measured one pixel before (after) a P pixel in the along-track direction are called NPB1 (NPA1) pixels. As these pixels are located near the precipitation area, it is more likely that they were inside the precipitation area for a short time before the measurement than NP pixels far away from precipitation area. If they were, in fact, inside the precipitation, the surface soil moisture would be higher, and a positive $\Delta \sigma^0_m$ value would be observed. Thus, the fact that $\Delta \sigma^0_m$ was positive in a large part of the land area, with the exception of tropical forests, such as Amazonia, and deserts, such as the Sahara Desert (Figs. 7a and 7b of SI07) indicates that this quantity is positively correlated with the anomaly of surface soil moisture. It was also found that $\Delta \sigma^0_m$ is higher at NPB1 pixels than at NPA1 pixels at midlatitudes, but the opposite is true in the Sahel of Africa in the tropics (Fig. 7c of SI07). This could be because an NPB1 (NPA1) pixel is likely to be located west
(east) of the precipitation area. Thus, in midlatitude areas, where the storm system usually moves from the west to the east, the probability that a pixel is inside the precipitation area for a short time before the measurement is higher at NPB1 pixels than at NPA1 pixels. Meanwhile, in the tropics, the storm system usually moves from east to west, making the reverse true.

2) KUPR

The same analysis that was used in SI07 was applied to the KuPR data to check whether KuPR shows soil moisture effects similar to those found for the PR. For the NPB1 and NPA1 pixels of KuPR, $\Delta \sigma_0^m$ was averaged over 1° latitude × 1° longitude cells. In this analysis, if an NP pixel is between two P pixels in the along-track direction, it is taken neither as an NPB1 pixel nor as an NPA1 pixel. The spatial distribution of $\Delta \sigma_0^m$ at the NPB1 (NPA1) pixels is shown in Fig. 2a (Fig. 2b), where negative values of $\Delta \sigma_0^m$ are shown in blue. In large portions of the land area, with the exception of forest, desert, and high mountains, the $\Delta \sigma_0^m$ is positive for both NPB1 and NPA1 pixels. It is worth noting, however, that vegetation and snow cover can degrade the relationship between the surface soil moisture and the surface backscattering cross sections. Between 35°S and 35°N, the results are similar to those of the PR. Figure 2c shows the differences between Figs. 2a and 2b, in which the blue (red) color indicates that $\Delta \sigma_0^m$ is higher at the NPB1 (NPA1) pixels. Note that blue areas mainly occur at midlatitudes and red areas occur in the Sahel of Africa. However, this difference is not as distinct as in the case of the PR. Some cells along the coastline or over remote islands show large absolute values of the difference in $\Delta \sigma_0^m$ if the number of samples is not large. Figure 2d shows the zonal mean of the $\Delta \sigma_0^m$ for the NPB1 and NPA1 pixels. With the exception of the region near 60°S, where the number of pixels is small, the zonal mean of $\Delta \sigma_0^m$ is positive. Moreover, the NPB1 pixels have higher $\Delta \sigma_0^m$ values than the NPA1 pixels at midlatitudes, but they have nearly the same $\Delta \sigma_0^m$ in the tropics.

As the orbit inclination angle of the TRMM satellite is 35°, the orbit track passes the precipitation area in a nearly west to east direction (Fig. 3a). In this case, an NPB1 (NPA1) pixel is likely to be located west (east) of the precipitation area. However, as the orbit inclination angle of the GPM core satellite is 65°, an orbit track passes the precipitation area from the southwest to northeast direction (in ascending orbit) or from the northwest to southeast direction (in descending orbit) rather than from a more west to east direction (Fig. 3b). In an ascending orbit, an NPB1 (NPA1) pixel is likely to be located south (north) of the precipitation area. Meanwhile, the opposite is true in a descending orbit. The difference in the satellite orbit inclination angle is the main reason that Fig. 2c is different from Fig. 7c of SI07. These general rules apply up to 50°. At higher latitude, an orbit track passes the precipitation area in a west to east direction rather than in a north to south or south to north direction.

Considering this difference, the NP pixels adjacent to a P pixel in the cross-track direction were obtained for KuPR (Fig. 3c). These pixels may be located either west or east of the precipitation area. In particular, NP pixels located one pixel to the left (right) of a P pixel in an ascending (descending) orbit are likely to be located west of the precipitation area. These pixels are called NPW1 pixels. Conversely, NP
pixels located one pixel to the right (left) of a P pixel in an ascending (descending) orbit are likely to be located east of the precipitation area. These pixels are called NPE1 pixels. If an NP pixel is between two P pixels in the cross-track direction, the pixel is taken neither as an NPW1 pixel nor as an NPE1 pixel. At the scan edge, some NPW1 and NPE1 pixels can be missed if a precipitation area exists close to the scan but does not overlay the scan. This may affect the quality of analysis. The average $\Delta \sigma_m^{P1}$ at the NPW1 (NPE1) pixels for 1° latitude × 1° longitude was calculated, and the spatial distribution is shown in Fig. 4a (Fig. 4b). Similar to Figs. 2a and 2b, positive $\Delta \sigma_m^{P1}$ values were observed over land, with the exception of forest, desert, and high mountains. Figure 4c shows the differences between Figs. 4a and 4b. The blue (red) color shows that the $\Delta \sigma_m^{P1}$ is higher for the NPW1 (NPE1) pixels. At midlatitude, the $\Delta \sigma_m^{P1}$ at the NPW1 pixels are higher. However, in the Sahel of Africa, the $\Delta \sigma_m^{P1}$ values at the NPE1 pixels are higher. The difference in the Sahel of Africa can be observed clearly as shown in Fig. 7c of SI07. Moreover, Fig. 4d shows the zonal mean of $\Delta \sigma_m^{P1}$ for the NPW1 and NPE1 pixels. The NPW1 pixels show a higher $\Delta \sigma_m^{P1}$ than the NPE1 pixels at midlatitudes, whereas the NPE1 pixels show a higher $\Delta \sigma_m^{P1}$ than the NPW1 pixels around 10°N. Based on these findings, it is confirmed that KuPR shows a soil moisture effect similar to that of PR.

3) KAMS

In this subsection, we examine whether the KaPR has a similar sensitivity to soil moisture as the KuPR. Using the same analysis as that used for KuPR, NP pixels adjacent to a P pixel in the cross-track direction were obtained, and the $\Delta \sigma_m^{K1}$ values of KaMS were analyzed. As KuPR has a better minimum detection level (15.46 dBZ) than that of KaMS (19.18 dBZ) and KuPR is always available at matched pixels, the precipitation judgment from the KuPR data was used to define NP and P pixels for the analysis of the KaMS measurements.

The average $\Delta \sigma_m^{K1}$ at the NP pixels adjacent to a P pixel in the cross-track direction was calculated over 1° latitude × 1° longitude cells. To reduce the number of figures, the NPW1 and NPE1 pixels were not separated while the difference in $\Delta \sigma_m^{K1}$ between NPW1 and NPE1 is similar to those for KuPR. The spatial distribution is shown in Fig. 5a. The area with positive $\Delta \sigma_m^{K1}$ values is limited compared with the KuPR results shown in Figs. 4a and 4b. Figure 5b shows the $\Delta \sigma_m^{K1}$ values instead of the $\Delta \sigma_m^{P1}$ values. Here, the area with positive $\Delta \sigma_m^{K1}$ values is slightly larger than that in Fig. 5a. Meanwhile, Fig. 5c shows $\Delta \sigma_m^{K1}$ minus $\Delta \sigma_m^{P1}$, revealing a difference as small as zero in the tropics, and a difference of 0.5 dB at midlatitudes. Figure 5d shows the zonal mean values of $\Delta \sigma_m^{K1}$ and $\Delta \sigma_m^{P1}$. In general, $\Delta \sigma_m^{K1}$ was negative in most of the latitude zones. Further, $\Delta \sigma_m^{K1}$ was larger than $\Delta \sigma_m^{P1}$ at midlatitudes, but negative in the tropics and around 60°N.

Subtracting Eq. (8) from Eq. (11) and using Eqs. (9) and (10), Eq. (15) is obtained:
The fact that \( D_s^0 \) is larger than \( D_m^0 \) indicates that \( A_{np} \) is larger at the NP pixels adjacent to a P pixel than at normal NP pixels. Thus, it is reasonable to assume that \( A_{np} \) is higher near the precipitation area.

\[
\Delta \sigma_n^0 - \Delta \sigma_m^0 = A_{np} - \overline{A_{np}}.  
\]  
(15)

Regarding KaMS, as nonprecipitation attenuation is larger than that for KuPR, correction for nonprecipitation attenuation is necessary. However, \( \Delta \sigma_n^0 \) is negative in some regions, which cannot be explained by the soil moisture effect. A possible reason for this is that the nonprecipitation attenuation is not well corrected in \( \Delta \sigma_n^0 \).
4) ANGLE BIN DEPENDENCE

Figure 6 shows the angle bin dependence of $D_s^0_m$ and $D_s^0_n$ at the NP pixels adjacent to a P pixel in the cross-track direction. For KuPR, the $D_s^0_m$ and $D_s^0_n$ in inner swath are slightly larger than those in outer swath. For KaMS, $D_s^0_m$ and $D_s^0_n$ are larger at nadir and are smaller at the edge of the inner swath. At the edge of the normal scan, some NPW1 and NPE1 pixels may be missed, but the effects of this on $D_s^0_m$ and $D_s^0_n$ are not clearly seen.

b. NP pixels near a P pixel

In this subsection, the analysis was extended to NP pixels located within eight pixels from a P pixel. At NP pixels located $l$ (1–8) pixels away from the nearest P pixel in the along-track direction, the averages of $\Delta \sigma_m^0$ and $\Delta \sigma_n^0$ between 50°S and 50°N were calculated for each $l$. If the distance from an NP pixel to the nearest P pixel is the same for the two directions, the NP pixel is excluded from the analysis. The situation as illustrated in Fig. 3 is valid in this latitude zone. In Fig. 7a, the solid (dotted) lines represent $\Delta \sigma_m^0$ ($\Delta \sigma_n^0$) and the bar shows $\Delta \sigma_m^0 - \Delta \sigma_n^0$, where the blue (red) color is used for KuPR (KaMS). The KuPR analysis is limited to angle bin numbers 13–37 in order to ensure that the KuPR and KaMS results are obtained under the same conditions. Figure 7b is the same as Fig. 7a, except the distance from the nearest P pixel is measured in the cross-track direction.

For KuPR, as $\Delta \sigma_n^0 - \Delta \sigma_m^0$ is as small as approximately 0.01 dB, it can be confirmed that nonprecipitation attenuation does not hinder the analysis of the soil moisture effect. In the along-track direction, the $\Delta \sigma_m^0$ decreases as the distance increases from 0.25 dB ($l = 1$) to 0.14 dB ($l = 8$). Meanwhile, in the cross-track direction, $\Delta \sigma_m^0$ is not strongly dependent on the distance and it maintains a value of approximately 0.25 dB up to $l = 8$. In the case of PR, as shown in Fig. 6 of SI07, $\Delta \sigma_m^0$ is not strongly dependent on the distance in the along-track direction. These results suggest that the soil moisture effect weakens more significantly with increasing distance in the north-to-south direction than in the west-to-east direction.

Regarding KaMS, $\Delta \sigma_n^0 - \Delta \sigma_m^0$ is nearly 0.1 dB, which is larger than that for KuPR. In the along-track direction, the
\( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) at \( l = 1 \) are \(-0.08\) and \(0.00\) dB, respectively, and both increase slowly with increasing distance. Meanwhile, at \( l = 8 \), \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) are \(0.02\) and \(0.07\) dB, respectively. In the cross-track direction, \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) at \( l = 1 \) are \(-0.07\) and \(0.02\) dB, respectively, and increase rapidly with distance, reaching values of \(0.10\) and \(0.16\) dB at \( l = 8 \), respectively. The increase in \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) with distance cannot be explained by the soil moisture effect.

We assume that the real \( \Delta \sigma_m^0 \) of KaMS decreases with distance as that of KuPR in the along-track direction. The real \( A_{\text{up}} \) is also assumed to decrease with distance, while the estimated \( A_{\text{up}} \) does not decrease significantly with distance. Figure 8 illustrates the situation. At \( l = 1 \), \( A_{\text{up}} \) and \( \Delta \sigma_n^0 \) are larger than those at \( l = 8 \), respectively. If the estimated \( A_{\text{up}} \) at \( l = 1 \) is underestimated and is the same as that at \( l = 8 \), then the calculated \( \Delta \sigma_n^0 \) at \( l = 1 \) is smaller than that at \( l = 8 \). This is an interpretation of the results in Fig. 7. As \( A_{\text{up}} \) is estimated by the environmental grid dataset with a spatial resolution of 0.5° latitude \( \times \) 0.5° longitude, it may be difficult to estimate the change in \( A_{\text{up}} \) over the eight fields of view (approximately 40 km). Nevertheless, as the real \( A_{\text{up}} \) or \( \Delta \sigma_n^0 \) are not obtained, we cannot establish a soil moisture effect in the KaPR data.

c. NP pixels measured shortly after a precipitation event

The Global Satellite Mapping of Precipitation (GSMaP) Microwave–IR Combined Product (GSMaP_MVK version 7; Kubota et al. 2020b) was used to identify NP pixels measured shortly after a precipitation event. GSMaP_MVK has a spatial resolution of 0.1° latitude \( \times \) 0.1° longitude and a temporal resolution of 1 h. As the target area of GSMaP_MVK is from 60°S to 60°N, the analysis was performed in this latitude zone. When GSMaP_MVK estimates precipitation rates higher than 0.1 mm h\(^{-1}\), the 1-h period is regarded as a wet period. Times at which the rate is lower than the threshold are regarded as dry periods. Based on this, the dry period duration after a precipitation event was calculated. If an NP pixel is measured when the dry period duration is 1 h, the pixel is called an NPT1 pixel.

\( \Delta \sigma_n^0 \) values at the NPT1 pixels were averaged over 1° latitude \( \times \) 1° longitude cells. Figure 9a shows the \( \Delta \sigma_m^0 \) of KuPR at the NPT1 pixels. \( \Delta \sigma_m^0 \) is positive in many of the grids over land, except for those over forests and deserts. Figure 9b shows the \( \Delta \sigma_m^0 \) values of the KaMS measurements at the NPT1 pixels, revealing that they are positive in many of the grids over land, but the values are smaller than those of KuPR. Figure 9c shows the \( \Delta \sigma_m^0 \) of KaHS at the NPT1 pixels. The results are similar to those of the KaMS. Furthermore, Fig. 9d shows the zonal mean values of \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) for KuPR, KaMS, and KaHS. KuPR’s \( \Delta \sigma_m^0 \) at the NPT1 pixels is higher than those at the NPB1, NPA1, NPW1, and NPE1 pixels shown in Figs. 2d and 4d particularly around 10°N. Thus, the probability that the NPT1 pixels were inside the precipitation area just before the measurement should be higher than that of the other pixels. Further, the soil moisture effect is more distinct at the NPT1 pixels. KaMS’s \( \Delta \sigma_m^0 \) values at the NPT1 pixels are higher than those at the NPW1 and NPE1 pixels, as shown in Fig. 5d, suggesting that nonprecipitation attenuation at the NPT1 pixels is smaller than that at the NPW1 and NPE1 pixels. KaMS’s \( \Delta \sigma_m^0 \) values at the NPT1 pixels are smaller than those of KuPR by 0.1–0.3 dB. The \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) values of KaHS are similar to those of KaMS.

In addition, the analysis was extended to NP pixels measured when the dry period duration (denoted by \( t \)) is 1–24 h. The global averages of the \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) were calculated for \( t \) from 1 to 24 h (Fig. 10). For KuPR, the \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) values were similar, and decreased with increasing \( t \). Meanwhile, for KuPR, the \( \Delta \sigma_m^0 \) was 0.30 dB at \( t = 1 \) h and 0.08 dB at \( t = 24 \) h. For KaMS, \( \Delta \sigma_m^0 \) decreased with increasing \( t \), from 0.19 dB at \( t = 1 \) h to 0.02 dB at \( t = 24 \) h. Thus, \( \Delta \sigma_m^0 \) was smaller than \( \Delta \sigma_n^0 \) by approximately 0.1 dB at \( t = 1 \) h, while \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) become closer with increasing \( t \) and are almost the same at \( t = 18 \) h. This indicates that \( A_{\text{up}} \) is larger than the nominal value at \( t = 1 \) h, but decreases toward the background value with increasing \( t \). As the temporal resolution of the environmental grid dataset was 6 h, changes in the \( A_{\text{up}} \) within 24 h should be reliable. As the KaMS’s \( \Delta \sigma_m^0 \) is nearly zero at \( t = 24 \) h, the soil moisture effect of KaMS appears to last for approximately 24 h after a precipitation event. Further, KaHS’s \( \Delta \sigma_m^0 \) and \( \Delta \sigma_n^0 \) values are nearly the same as those of KaMS.

3. Analysis of soil moisture effect at P pixels

In this section, the \( \Delta \sigma_m^0(M) \) estimates at the P pixels are analyzed. \( \Delta \sigma_m^0(SRT) \), \( \Delta \sigma_m^0(FA) \), \( \Delta \sigma_m^0(BA) \), and \( \Delta \sigma_m^0(\text{TR}) \) were analyzed to determine if the SRT is affected by soil moisture. \( A_s(SRT) \) was estimated using Eq. (7) and \( A_p(FA) \), \( A_p(\text{BA}) \), and \( A_p(\text{TR}) \) were estimated using Eq. (A4).

\( A_{\text{up}}[X] \) and \( A_{\text{up}}[\hat{X}] \) in Eqs. (7) and (A4) are difficult to obtain as they are not stored in the standard product. Thus, they are approximately given as follows.

- \( A_{\text{up}}[X] \) (for FA) is replaced by \( A_{\text{up}} \) at the NP pixel measured 1 pixel before the precipitation area that includes the target P pixel.
- \( A_{\text{up}}[X] \) (for BA) is replaced by \( A_{\text{up}} \) at the NP pixel measured 1 pixel after the precipitation area that includes the target P pixel.

Unauthenticated | Downloaded 01/10/24 02:49 AM UTC
• $A_{np}[X]$ (for TR) is replaced by the $A_{np}$ from the same grid, month, and angle bin in which the target P pixel is contained.
• $A_{np}[X]$ is replaced by the simple average of $A_{np}[X_1]$ and $A_{np}[X_2]$.

Another estimate of $\Delta\sigma^0_p$ using a method independent of the SRT is required to evaluate the $\Delta\sigma^0_p(\text{SRT})$, $\Delta\sigma^0_p(\text{FA})$, $\Delta\sigma^0_p(\text{BA})$, and $\Delta\sigma^0_p(\text{TR})$. $A_p$ can be estimated using the Hitschfeld–Bordan (HB; Hitschfeld and Bordan 1954) method as follows:

$$A_p = -\frac{10}{\beta} \log_{10}(1 - \xi),$$

(16)

where

$$\xi = 0.2(\ln 10)\beta \int_0^r \alpha(r)Z_m^0(r)dr,$$

(17)

where $Z_m$ is the measured radar reflectivity factor, $r$ is the distance from the radar, and $r_s$ is the value of $r$ at the surface. In addition, $\alpha$ and $\beta$ are the coefficients of the $k$–$Z_r$ relation as follows:

$$k(r) = \alpha(r)Z_r^\beta(r),$$

(18)

where $k$ is the specific attenuation and $Z_r$ is the attenuation-corrected radar reflectivity factor. This calculation was performed

**Table 1. Range of $R$ for precipitation rate categories.**

<table>
<thead>
<tr>
<th>Category</th>
<th>$R$ (mm h$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$0 &lt; R \leq 0.5$</td>
</tr>
<tr>
<td>2</td>
<td>$0.5 &lt; R \leq 1$</td>
</tr>
<tr>
<td>3</td>
<td>$1 &lt; R \leq 2$</td>
</tr>
<tr>
<td>4</td>
<td>$2 &lt; R \leq 4$</td>
</tr>
<tr>
<td>5</td>
<td>$4 &lt; R \leq 8$</td>
</tr>
<tr>
<td>6</td>
<td>$8 &lt; R \leq 16$</td>
</tr>
<tr>
<td>7</td>
<td>$16 &lt; R \leq 32$</td>
</tr>
<tr>
<td>8</td>
<td>$32 &lt; R \leq 64$</td>
</tr>
<tr>
<td>9</td>
<td>$64 &lt; R \leq 300$</td>
</tr>
</tbody>
</table>

**Fig. 9.** Spatial distribution of $\Delta\sigma^0_p$ (dB) at NPT1 pixels for (a) KuPR, (b) KaMS, and (c) KaHS. Blue means $\Delta\sigma^0_p$ is negative. (d) The zonal means of $\Delta\sigma^0_m$ (solid lines; in dB) and $\Delta\sigma^0_n$ (dotted lines; in dB) at NPT1 pixels. Blue, red, and green lines represent KuPR, KaMS, and KaHS, respectively.

**Fig. 10.** Relationship between the global averages of $\Delta\sigma^0_m$ (solid lines; in dB), $\Delta\sigma^0_n$ (dotted lines; in dB), and $\Delta\sigma^0_n - \Delta\sigma^0_m$ (bars) at NP pixels and the dry period duration. Blue, red, and green denote KuPR, KaMS, and KaHS, respectively.
in the SRT module (Meneghini et al. 2021). The value of Eq. (16) is denoted by \( A_p^{(HB)} \). Using HB as \( M \) in Eqs. (13) and (14), \( D_{0e}^{(HB)} \) is obtained.

A hybrid estimate of \( A_p \) by the HB and SRT methods is given in the SRT module, which is denoted by \( A_p^{(HYB)} \). Moreover, in the Solver module, \( A_p^{(SLV)} \) is given as the final estimate of \( A_p \), as explained before. Using HYB and SLV as \( M \) in Eqs. (13) and (14), \( D_{0e}^{(HYB)} \) and \( D_{0e}^{(SLV)} \) are obtained. As \( A_p^{(HYB)} \) and \( A_p^{(SLV)} \) are not independent of \( A_p^{(SRT)} \), \( D_{0e}^{(HYB)} \) and \( D_{0e}^{(SLV)} \) will be shown just as reference.

The soil moisture effect may depend on the precipitation rate as the surface soil moisture increases with increasing precipitation rate. To investigate the dependence of \( D_{0e}^{(p)} \) on the precipitation rate, \( P \) pixels were categorized by the surface precipitation rate estimates (variable name is precipRateESurface; denoted by \( R \)) of the KuPR algorithm. \( R \) is categorized as listed in Table 1. For each category, the global averages of \( D_{0e}^{(p)} \), \( D_{0e}^{(p)(HB)} \), \( D_{0e}^{(p)(HYB)} \), \( D_{0e}^{(p)(SLV)} \), and \( D_{0e}^{(p)(SRT)} \) for each precipitation rate category. The units are dB. (b),(d) \( D_{0e}^{(p)(FA)} \), \( D_{0e}^{(p)(BA)} \), and \( D_{0e}^{(p)(TR)} \) are shown in addition and the ranges of \( D_{0e}^{(p)} \) estimates are limited to between \(-2\) and \(2\) dB. (a),(b) KuPR with angle bin numbers 13–37, and (c),(d) KaMS.

**Fig. 11.** Global averages of \( D_{0e}^{(p)} \), \( D_{0e}^{(p)(HB)} \), \( D_{0e}^{(p)(HYB)} \), \( D_{0e}^{(p)(SLV)} \), and \( D_{0e}^{(p)(SRT)} \) for each precipitation rate category. The units are dB. (b),(d) \( D_{0e}^{(p)(FA)} \), \( D_{0e}^{(p)(BA)} \), and \( D_{0e}^{(p)(TR)} \) are shown in addition and the ranges of \( D_{0e}^{(p)} \) estimates are limited to between \(-2\) and \(2\) dB. (a),(b) KuPR with angle bin numbers 13–37, and (c),(d) KaMS.
KuPR as the precipitation rate estimates by KaMS are generally not as reliable as those by KuPR.

As shown in Figs. 11a and 11b, the \( \Delta \sigma_0^0 \) is positive for categories 1–4 \((R < 4 \text{ mm h}^{-1}) \), and negative for categories 5–9. As the real \( \Delta \sigma_0^0 \) is larger than \( \Delta \sigma_0^0 \), it is positive for categories 1–4. Further, \( \Delta \sigma_0^0 \) (HB) is positive and increases with \( R \) for categories 1–4, while it decreases with \( R \) for higher categories, eventually becoming negative for categories 7–9. As the HB method is not reliable for heavy precipitation (Meneghini et al. 2021), \( \Delta \sigma_0^0 \) (HB) are probably underestimated for the higher categories.

\( \Delta \sigma_0^0 \) (FA) and \( \Delta \sigma_0^0 \) (BA) were positive in every category. As FA and BA reference NP pixels near the precipitation area, the NP pixels show, to some extent, the soil moisture effect. However, \( \Delta \sigma_0^0 \) (TR) is not to show the soil moisture effect, and it is slightly negative. The \( \Delta \sigma_0^0 \) (SRT) is positive, as are \( \Delta \sigma_0^0 \) (FA) and \( \Delta \sigma_0^0 \) (BA), but it is less than 1 dB, except for category 9, and smaller than \( \Delta \sigma_0^0 \) (HB) for categories 1–6. Moreover, \( \Delta \sigma_0^0 \) (SRT) is smaller than \( \Delta \sigma_0^0 \) for categories 1–4. These results confirm that the SRT of KuPR underestimates the soil moisture effect and must be corrected.

\( \Delta \sigma_0^0 \) (HYB) and \( \Delta \sigma_0^0 \) (SLV) take values between \( \Delta \sigma_0^0 \) (HB) and \( \Delta \sigma_0^0 \) (SRT). \( \Delta \sigma_0^0 \) (HYB) is close to \( \Delta \sigma_0^0 \) (HB), and it increases for categories 1–4, but decreases for higher categories. \( \Delta \sigma_0^0 \) (SLV) is close to \( \Delta \sigma_0^0 \) (SRT) for heavy precipitation and maintains a positive value for all categories.

Regarding KaMS, as shown in Fig. 11c, \( \Delta \sigma_0^0 \) is nearly zero for category 1 and negative for higher categories because of heavy precipitation attenuation. Moreover, \( \Delta \sigma_0^0 \) (HB) is positive for categories 1–4, nearly zero for category 5, and negative for categories 6–9. The negative value of \( \Delta \sigma_0^0 \) (HB) is the result of the underestimation of the HB method. Meanwhile, as shown in Fig. 11d, \( \Delta \sigma_0^0 \) (FA) and \( \Delta \sigma_0^0 \) (BA) are nearly zero for all categories, as the \( \sigma_0^0 \) values at NP pixels near the precipitation area are underestimated possibly because of an insufficient correction for nonprecipitation attenuation (as discussed in section 2b). In addition, \( \Delta \sigma_0^0 \) (TR) and \( \Delta \sigma_0^0 \) (SRT) were also approximately zero. These results confirm that the SRT of KaMS does not account for the soil moisture effect and must be corrected. \( \Delta \sigma_0^0 \) (HYB) and \( \Delta \sigma_0^0 \) (SLV) are similar to each other, and they are close to \( \Delta \sigma_0^0 \) (HB) for categories 1–4, but decrease for higher categories.

The spatial distributions of \( \Delta \sigma_0^0 \) (HB) and \( \Delta \sigma_0^0 \) (SRT) in category 4 are shown in Fig. 12. KuPR’s \( \Delta \sigma_0^0 \) (HB) is positive over almost all land areas, from slightly positive values in forests to values as high as 5 dB in some parts of the Sahel of Africa and Australia. KaMS’s \( \Delta \sigma_0^0 \) (HB) shows a spatial distribution similar to that of KuPR, but with smaller values. KuPR’s \( \Delta \sigma_0^0 \) (SRT) is positive in some regions, but it is much smaller than \( \Delta \sigma_0^0 \) (HB). KaMS’s \( \Delta \sigma_0^0 \) (SRT) is smaller than KuPR’s \( \Delta \sigma_0^0 \) (SRT).

4. Correction of PIA estimates and effects on precipitation rate estimates

The value of \( \delta \sigma_0^0 \) needs to be estimated to correct for \( A_p \) (SRT). Therefore, in this section, an estimation method is developed and implemented for the single-frequency algorithms of DPR. The modified algorithm was tested using a 1-month set of data, and the effects of the correction on the precipitation rate estimates were examined.

Though we have analyzed many candidates for \( \delta \sigma_0^0 \), \( \Delta \sigma_0^0 \) (HB) will be used for the correction. In section 2, the behavior of \( \delta \sigma_0^0 \) and \( \Delta \sigma_0^0 \) at NP pixels clearly shows evidence of a soil moisture effect. Nevertheless, correction for this effect would yield estimates that are smaller than those given by \( \Delta \sigma_0^0 \) (HB). This suggests that the soil moisture effect is only one part of the error in the SRT and that the fluctuations in the surface cross section limit the accuracy of the method, particularly over land at Ku band. The estimates \( \Delta \sigma_0^0 \) (HYB)
and $\Delta\sigma^0_e$(SLV), shown as references in section 3, should not be used to correct the SRT, however, as they themselves depend on the SRT.

### a. Database

$\delta\sigma^0_e = \sigma^o_e[P] - \sigma^o_e[X]$ can be rewritten as $\delta\sigma^0_e = \Delta\sigma^0_e[P] - \Delta\sigma^0_e[X]$ by subtracting $\sigma^o_e$ from both terms. $\Delta\sigma^0_e$(HB) and $\Delta\sigma^0_e$(SRT) can be used for estimates of $\Delta\sigma^0_e[P]$ and $\Delta\sigma^0_e[X]$, respectively, but it must be kept in mind that $\Delta\sigma^0_e$(HB) is underestimated in heavy precipitation. Using a 5° latitude × 5° longitude grid, the $\Delta\sigma^0_e$(HB) and $\Delta\sigma^0_e$(SRT) are averaged over each precipitation rate category (Table 1), and angle bin group (Table 2).

Figure 13 shows the $\Delta\sigma^0_e$(HB) and $\Delta\sigma^0_e$(SRT) values for each precipitation rate category at grid (100°–95°W, 30°–35°N) and angle bin group 1 as an example. $\Delta\sigma^0_e$(HB) and $\Delta\sigma^0_e$(SRT) are represented by black and purple circles, respectively. Open circles are used if the number of samples is less than 100. As shown in Fig. 13a, for KuPR, $\Delta\sigma^0_e$(HB) reaches a maximum in category 5, and decreases for categories greater than 6. Below category 5, $\Delta\sigma^0_e$ cannot be determined for all categories and no correction for $A_P$(SRT) is applied.

Figure 13b shows the results for KaMS, in which $\delta\sigma^0_e$ is determined in the same manner as for KuPR and is represented by the red area.

In general, the following procedures are applied for each grid and angle bin group to determine $\delta\sigma^0_e$:

- The maximum value of $\Delta\sigma^0_e$(HB) is searched among categories 1–9 (except for categories with a sample number of less than 100). If the category number with the maximum $\Delta\sigma^0_e$(HB) is $N_{\text{max}}$, $\Delta\sigma^0_e[P]$ is equal to $\Delta\sigma^0_e$(HB) for categories 1 to $N_{\text{max}}$ and $\Delta\sigma^0_e[P]$ is equal to the maximum value of $\Delta\sigma^0_e$(HB) for categories $N_{\text{max}} + 1$ to 9.
- $\Delta\sigma^0_e[X]$ is equal to the average of $\Delta\sigma^0_e$(SRT) for categories 1–9.
- $\delta\sigma^0_e$ is given by $\Delta\sigma^0_e[P] - \Delta\sigma^0_e[X]$. If the value is negative, it is replaced by 0.

- If the number of samples is fewer than 100 in all categories, $\delta\sigma^0_e$ cannot be determined for all categories and no correction for $A_P$(SRT) is applied.

The value of $\delta\sigma^0_e$ in category $N$ is denoted by $\delta\sigma^0_e[N]$. The $\delta\sigma^0_e[N]$ values for each category, grid, and angle bin have been compiled into a database.

Figure 14 shows the spatial variation of $\delta\sigma^0_e[9]$ for angle bin group 1 (Figs. 14a,b) and angle bin group 3 (Figs. 14c,d).
wherein Figs. 14a,c and 14b,d show the KuPR and KaMS results, respectively. A gray grid indicates that the number of samples is fewer than 100 in all categories and no correction for $A_p$(SRT) is applied. Only limited land pixels at small and remote islands are excluded from the correction. Note that $\delta \sigma_0^p[9]$ is higher in the Sahel of Africa, Australia, and the central part of the United States. KuPR and KaMS results are similar, but KuPR shows larger area of high $\delta \sigma_0^p[9]$. $\delta \sigma_0^p[9]$ is smaller at angle bin group 3 than at angle bin group 1.

Figure 15 is a cumulative histogram of the $\delta \sigma_0^p[N]$ value for angle bin group 1. Figure 15a shows the KuPR results. For some cells, $\delta \sigma_0^p[N]$ is zero. The lines of $\delta \sigma_0^p[N]$ for categories 6–9 are the same, suggesting that $\Delta \sigma_0^p$(HB) reaches a maximum in category 6 or lower. $\delta \sigma_0^p[9]$ is higher than 2 dB in nearly half of land grids. Figure 15b shows the KaMS results, revealing that the $\delta \sigma_0^p[9]$ values are similar to those of KuPR.

b. Algorithm modification

The single-frequency algorithms were modified to correct for $A_p$(SRT) by referencing the compiled database. In the first execution, the correction is not applied, and the tentative estimate of the surface precipitation rate is denoted by $R_1$ (mm h$^{-1}$). In the second execution, $\delta \sigma_0^p$ is given by referencing the database and $R_1$. As the precipitation category $N$ is for $2^{N-3} < R_1 < 2^{N-2}$, $\delta \sigma_0^p$ is set equal to $\delta \sigma_0^p[N]$ when $R_1 = 2^{N-2.5}$. For other $R_1$ values, $\delta \sigma_0^p$ is log-linearly interpolated with $R_1$, as follows:

$$
\delta \sigma_0^p = \begin{cases} 
\delta \sigma_0^p[1] \\
\delta \sigma_0^p[N + 1] \log_2(R_1) - (N - 2.5) + \delta \sigma_0^p[N](N - 1.5) - \log_2(R_1) \\
\delta \sigma_0^p[9]
\end{cases}
\quad (2^{N-2.5} < R_1 \leq 2^{N-15}; \quad N = 1 - 8).
\quad (19)
$$

The database of $\delta \sigma_0^p[N]$ was prepared for both KuPR and KaMS. For KaHS, the KaMS database was used because the effects of soil moisture on KaHS and KaMS are similar as described in section 2.

c. Effects on precipitation rate estimates

The modified single-frequency algorithms were applied to the DPR measurements from 467 orbits (orbit numbers 012826–013292) in June 2016. Then, the modified and original algorithms (version 06A) were compared for their surface precipitation rate estimates. Table 3 summarizes the unconditional average of $R$ (mm in 30 days) for all land pixels. For KuPR (angle bin numbers 1–49), $R$ is 59.97 mm in the original algorithm and 70.79 mm in the modified algorithm, which constitutes an increase of 18.0%. For the inner swath, the
The increase was 18.3% for KuPR, 15.1% for KaMS, and 13.5% for KaHS. According to Figs. 14–16, $\delta \sigma^0$ did not vary much between KuPR and KaMS. As the SRT is more reliable with KaMS than with KuPR, the change in $A_p$(SLV) should be larger for KaMS. On the other hand, the sensitivity of $R$ to the change of $A_p$(SLV) is higher for KuPR than for KaMS. Owing to these effects, the increases in $R$ are not very different between KuPR and KaMS.

The bottom figures in Fig. 17 show the scatterplots between $R$ in the original algorithm ($R_{org}$) and $R$ in the modified algorithm ($R_{mod}$). The red line is the average $R_{mod}$ for a 1 dB mm h$^{-1}$ bin of $R_{org}$. Meanwhile, the fractional change $| (R_{mod} - R_{org}) / R_{org} |$ for a 1 dB mm h$^{-1}$ bin of $R_{org}$ are shown in the upper figures of Fig. 17. In Fig. 17a, for KuPR, a change in $R$ is observed when $R_{org}$ is greater than 1 mm h$^{-1}$. The fractional change reached as high as 40% when $R_{org}$ was approximately 10 mm h$^{-1}$. 

Fig. 15. Cumulative histograms of the $\delta \sigma^0[N]$ value (dB) for angle bin group 1. (a) KuPR and (b) KaMS. For KuPR (KaMS), histograms for $N = 6–9$ (5–9) are mostly overlapped.

Fig. 16. Cumulative histograms of the $\delta \sigma^0[9]$ value (dB) for different angle bin groups. (a) KuPR (angle bin groups 1–6) and (b) KaMS (angle bin groups 1–3).
In Fig. 17b for KaMS and Fig. 17c for KaHS, changes in $R$ are observable even if $R_{\text{org}}$ is less than 1 mm h$^{-1}$ because the SRT of KaPR is more reliable than that of KuPR. Overall, the fractional change in $R$ was less than 20%. Moreover, the fractional change decreases when $R_{\text{org}}$ is approximately 100 mm h$^{-1}$. This is probably consequence of the fact that the SRT estimate is not available as the surface echo disappears because of strong attenuation. In the standard algorithm, the SRT is judged to be questionable and is not used if $A_p(\text{SRT})$ is more than 10 times as large as $A_p(\text{HB})$. In cases where the original $A_p(\text{SRT})$ is smaller than 10 times of $A_p(\text{HB})$ and the corrected $A_p(\text{SRT})$ is larger than 10 times of $A_p(\text{HB})$, $R_{\text{mod}}$ is estimated without the SRT and can be smaller than $R_{\text{org}}$.

For reference, the same correction method with PR version 7 algorithm was applied, in which $d_{0e}$ was set to be 0.5 dB for all pixels over land. $R$ in this test is denoted by $R_{\text{test}}$ and is higher than that in the original product by 5.6% for KuPR, 4.4% for KaMS, and 4.2% for KaHS, as listed in Table 3. Therefore, if the correction method developed in this study is applied to the standard algorithms of DPR or PR, the average precipitation rate estimates should increase.

Figure 18 shows the angle bin dependence of the unconditional average of $R_{\text{org}}$, $R_{\text{mod}}$, and $R_{\text{test}}$. The fractional changes $[(R_{\text{mod}} - R_{\text{org}})/R_{\text{org}}]$ and $[(R_{\text{test}} - R_{\text{org}})/R_{\text{org}}]$ are also shown in Fig. 18. For KuPR, $R_{\text{mod}}$ and $R_{\text{test}}$ as well as $R_{\text{org}}$ has strong angle bin dependence. At larger incidence angles, light precipitation is likely to be missed. At angle bins 20 and 30, $R$ is higher than the values at the neighboring angle bins due to side-lobe clutter effects. At near angle bin 25, $R$ is higher partly because SRT is unstable over land at nadir (Hirose et al. 2021). The fractional changes are not strongly dependent on the incidence angle except for $R_{\text{mod}}$ within angle bin group 1 (angle bins 21–29); they are larger at angle bins 21 and 29 and become smaller in approaching angle bin 25. It may be mitigated if $d_{0e}[N]$ is determined at each single angle bin. For KaMS and KaHS in Figs. 18b and 18c, respectively, $R$ exhibits the angle bin dependence but the fractional changes are not strongly dependent on the angle bin numbers.

5. Summary and conclusions

In this study, the soil moisture effect was analyzed for the DPR, and a correction method for $A_p(\text{SRT})$ that considers the soil moisture effect was developed. As discussed in section 2, for the KuPR, following the same analysis as in SI07, the soil moisture effect, or positive $D_{\text{sm}}$, was found for a large portion of land areas, with the exception of forests and deserts. For KaMS, in contrast to KuPR, the soil moisture effect was not clearly confirmed. As mentioned in section 3, $\Delta d_{0e}(\text{HB})$ increases with the precipitation rate for light precipitation, but decreases under heavy precipitation. The former result suggests a dependence of $\Delta d_{0e}$ on the precipitation rate,
whereas the latter is a result of the underestimation of the HB method. Moreover, $\Delta \sigma_0^0(SRT)$ was slightly positive for KuPR and nearly zero for KaMS. As $\Delta \sigma_0^0(HB)$ is larger than $\Delta \sigma_0^0(SRT)$ for light precipitation, it was confirmed that $A_p(SRT)$ must be corrected for the soil moisture effect. In section 4, the database of $\Delta \sigma_0^0$ was produced from $\Delta \sigma_0^0(HB)$ and $\Delta \sigma_0^0(SRT)$. Using the database, $R$ increased by 18.3% for KuPR (inner swath), 15.1% for KaMS, and 13.5% for KaHS, as compared with the original algorithm (version 06A). The correction method is implemented in the DPR standard algorithm version 07. For version 07, the database of $\Delta \sigma_0^0$ is prepared also for the full swath of KaPR after the scan pattern change in the same way with KuPR and the inner swath of KaPR. The value of $\Delta \sigma_0^0$ in the outer swath of KaPR is similar to that in the inner swath of KaPR.

Some issues remain to be solved. The correction method for the dual-frequency algorithm needs to be studied. In the DSRT, the soil moisture effect was expected to be small in $A_d$, as it is canceled by taking the difference between KuPR and KaPR. Therefore, a more accurate analysis is necessary to correct $A_d$. Another issue concerns the HB method. For $A_p(HB)$, a fixed $k–Z_e$ relation is assumed and nonuniform beam filling effects are not considered. For heavy precipitation, as the HB method is unreliable, $\Delta \sigma_0^0(HB)$ is discarded and the dependence of $\Delta \sigma_0^0$ on precipitation rate is neglected for heavy precipitation. This may result in an underestimation of the heavy precipitation rates. A combined algorithm with DPR and GPM Microwave Imager (GMI) to estimate $\sigma_0^0$ will be considered in future work. As the soil moisture can be estimated by microwave radiometers (e.g., Turk et al. 2014), data from the GMI may help improve estimates of surface soil moisture and $\Delta \sigma_0^0$.

**Acknowledgments.** This work was a result of Precipitation Measurement Mission of NASA and JAXA. It is financially supported by JAXA under Second Research Announcement on the Earth Observations. Seto would like to thank Prof. Taikan Oki at The University of Tokyo for encouraging him in the study on soil moisture retrieval using TRMM data, which became a basis of this study.

**Data availability statement.** GPM DPR standard products (version 06A) used in this study are openly available through from NASA Goddard Earth Sciences Data and Information Services Center at [https://doi.org/10.5067/GPM/DPR/Ku/2A/06](https://doi.org/10.5067/GPM/DPR/Ku/2A/06) and [https://doi.org/10.5067/GPM/DPR/Ka/2A/06](https://doi.org/10.5067/GPM/DPR/Ka/2A/06). GSMaP–MVK product (version 7) used in this study is openly available through JAXA Global Rainfall Watch ([https://sharaku.eorc.jaxa.jp/GSMaP/index.htm](https://sharaku.eorc.jaxa.jp/GSMaP/index.htm)).

**APPENDIX**

**Derivation of $A_p$ in SRT**

For notational convenience, the reference methods are renamed SRT, where SRT1 is “FA,” SRT2 is “BA,” and SRT3 is “TR.” The PIA estimate in SRT, is given in Eq. (A1):

$$A(SRT_i) = \sigma_{0m}[X_i] - \sigma_{0p}[P],$$

where a variable with $[X_i]$ denotes that the value is the average for the NP pixels used in SRT, $\sigma_{0m}[X_i]$ is decomposed, as expressed in Eq. (A2):

$$\sigma_{0m}[X_i] = A_p[X_i] - A_{np}[X_i].$$
By substituting Eqs. (A2) and (2) into Eq. (A1), Eq. (A3) can be obtained:

\[
A(\text{SRT}) = A_p + A_{ap}[P] - A_{ap}[X] - \left(\sigma_R^0[P] - \sigma_R^0[X]\right).
\]  
(A3)

As in the Solver module, the terms of \(\sigma_R^0[P] - \sigma_R^0[X]\) are assumed to be zero and \(A_p\) is estimated as in Eq. (A4):

\[
A_p(\text{SRT}) = A(\text{SRT}) + A_{ap}[X] - A_{ap}[P].
\]  
(A4)

The three \(A(\text{SRT})\) estimates are combined into a single estimate, \(A(\text{SRT})\), as shown in Eq. (A5):

\[
A(\text{SRT}) = \sum_{i=1}^{3} w(\text{SRT})_i A(\text{SRT})_i,
\]  
(A5)

where \(w(\text{SRT})_i\) is the weight factor for \(\text{SRT}_i\) and Eq. (A6) always holds:

\[
\sum_{i=1}^{3} w(\text{SRT})_i = 1.
\]  
(A6)

By substituting Eq. (A1) for \(i = 1\)–3 into Eq. (A5) and using Eq. (A6), Eq. (A7) is obtained:

\[
A(\text{SRT}) = \left\{ \sum_{i=1}^{3} w(\text{SRT})_i \sigma_R^0[X_i] \right\} - \sigma_R^0[P].
\]  
(A7)

By defining \(\sigma_R^0[X]\) as in Eq. (A8), Eq. (A7) becomes Eq. (1):

\[
\sigma_R^0[X] \equiv \sum_{i=1}^{3} w(\text{SRT})_i \sigma_R^0[X_i].
\]  
(A8)

By substituting Eq. (A3) for \(i = 1\)–3 into Eq. (A5), Eq. (A9) is obtained:

\[
A(\text{SRT}) = A_p + A_{ap}[P] - \left\{ \sum_{i=1}^{3} w(\text{SRT})_i A_{ap}[X_i] \right\} - \sigma_R^0[P] + \left\{ \sum_{i=1}^{3} w(\text{SRT})_i \sigma_R^0[X_i] \right\}.
\]  
(A9)

By defining \(A_{ap}[X]\) and \(\sigma_R^0[X]\) as in the following equations, Eq. (A9) becomes Eq. (6):

\[
A_{ap}[X] \equiv \sum_{i=1}^{3} w(\text{SRT})_i A_{ap}[X_i]
\]  
(A10)

and

\[
\sigma_R^0[X] \equiv \sum_{i=1}^{3} w(\text{SRT})_i \sigma_R^0[X_i].
\]  
(A11)

REFERENCES


