Cloud Assumption of Precipitation Retrieval Algorithms for the Dual-Frequency Precipitation Radar

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ABSTRACT: An assumption related to clouds is one of uncertain factors in precipitation retrievals by the Dual-Frequency Precipitation Radar (DPR) on board the Global Precipitation Measurement (GPM) *Core Observatory*. While an attenuation due to cloud ice is negligibly small for Ku and Ka bands, attenuation by cloud liquid water is larger in the Ka band and estimating precipitation intensity with high accuracy from Ka-band observations can require developing a method to estimate the attenuation due to cloud liquid water content (CLWC). This paper describes a CLWC database used in the DPR level-2 algorithm for the GPM V06A product. In the algorithm, the CLWC value is assumed using the database with inputs of precipitation-related variables, temperature, and geolocation information. A calculation of the database was made using the 3.5-km-mesh global atmospheric simulation derived from the Nonhydrostatic Icosahedral Atmospheric Model (NICAM) global cloud-system-resolving model. Impacts of current CLWC assumptions for surface precipitation estimates were evaluated by comparisons of precipitation retrieval results between default values and 0 mg m^{-3} of the CLWC. The impacts were quantified by the normalized mean absolute difference (NMAD) and the NMAD values showed 2.3% for the Ku, 9.9% for the Ka, and 6.5% for the dual-frequency algorithms in global averages, while they were larger in the tropics than in high latitudes. Effects of the precipitation estimates from the CLWC assumption were examined further in terms of retrieval processes affected by the CLWC assumption. This study emphasizes the CLWC assumption provided more effects on the precipitation estimates through estimating path-integrated attenuation due to rain.

KEYWORDS: Algorithms; Radars/Radar observations; Satellite observations

1. Introduction

The Dual-Frequency Precipitation Radar (DPR) on board the Global Precipitation Measurement (GPM) *Core Observatory* was launched in February 2014 (Hou et al. 2014; Skofronick-Jackson et al. 2017). The DPR expands the coverage of observations to include higher latitudes than those that are obtained by the Precipitation Radar (PR) on board the Tropical Rainfall Measuring Mission (TRMM) (Kummerow et al. 1998; Kozi et al. 2001). In addition, the DPR measures precipitation via higher-sensitivity observations than those of the TRMM PR (Hamada and Takayabu 2016; Masaki et al. 2020, manuscript submitted to *IEEE Trans. Geosci. Remote Sens.*) and provides drop size distribution (DSD) information based on the differential scattering properties at the two frequencies (Seto et al. 2013; Liao and Meneghini 2019; Yamaji et al. 2020). The DPR

consists of a Ku-band (13.6 GHz) precipitation radar (KuPR) and a Ka-band (35.5 GHz) precipitation radar (KaPR) (Kojima et al. 2012; Iguchi 2020).

In generating precipitation datasets, it is necessary to develop computationally efficient, fast-processing DPR level-2 (L2) algorithms that can provide estimated precipitation rates, radar reflectivity factors, and precipitation information, such as the DSD and precipitation type (Kubota et al. 2014; Iguchi et al. 2018; Iguchi 2020). In the L2 algorithms, an assumption related to clouds is one of uncertain factors; the algorithm assumes cloud liquid water content (CLWC). While an attenuation due to cloud ice is negligibly small for Ku and Ka bands, attenuation by the CLWC is larger in the Ka band than in the Ku band, as known in previous works (e.g., Meneghini and Kozu 1990). Therefore, estimating precipitation intensity with high accuracy from KaPR observations can require developing a method to estimate the attenuation due to CLWC and incorporate it into the algorithm.

CLWC assumptions are common to spaceborne radar precipitation retrievals and regional atmospheric simulations and observational data have been utilized in previous works.

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The 2A25 algorithm for the TRMM PR assumed the attenuation by CLWC based on the result of a numerical simulation of storms with a cloud-system-resolving model (CRM) (Iguchi et al. 2009). The vertical distributions of cloud liquid water in each radar profile were described using Weather Research and Forecasting (WRF) Model simulations in the GPM combined algorithm, which provides precipitation estimates using both the DPR and the GPM Microwave Imager (GMI) (Greco et al. 2016). In rainfall retrievals over the ocean with the *CloudSat* Cloud Profiling Radar (CPR), a spaceborne W-band radar, the CLWC was based on estimates of the cloud liquid water path (CLWP) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) products collocated with raining CPR pixels (Haynes et al. 2009).

Recently, high-resolution global atmospheric simulations have been done using a global cloud-system-resolving model (GCRM) (Stevens et al. 2019). The GCRM explicitly calculates moisture convection using a microphysical cloud scheme. The development of the GCRM was pioneered by the Nonhydrostatic Icosahedral Atmospheric Model (NICAM) (Satoh et al. 2014).

The DPR-L2 algorithm uses a correction method for attenuation by CLWC that was developed using 3.5-km-mesh NICAM simulation data. Preliminary results of the CLWC assumption using the NICAM data were described in Kubota et al. (2012). This paper describes the CLWC database used with the latest DPR-L2 algorithms. The paper also evaluates the CLWC assumptions made in experiments by altering the use of CLWC data in the DPR-L2 algorithms and comparing results to the standard data. Section 2 describes the data and methods related to the GPM DPR data and algorithms, NICAM data, construction of the CLWC database, and utilization of the CLWC database in the algorithms. Section 3 evaluates the effectiveness of using the CLWC assumption with the DPR-L2 algorithms. Section 4 examines retrieval processes affected by the CLWC assumption in the algorithms. Section 5 presents summaries and discussion of this research.

2. Data and method

a. GPM DPR instruments and algorithms

The DPR is the space-based Dual-Frequency Precipitation Radar on board the GPM *Core Observatory*. The DPR was developed jointly by the Japan Aerospace Exploration Agency (JAXA) and the National Institute of Information and Communications Technology (NICT) (Kojima et al. 2012; Iguchi 2020). Its horizontal resolution is 5 km. The KuPR swath width is approximately 245 km. The swath width for the matched scan beams of the KaPR is approximately 125 km, and is marked as “MS.” For comparisons among DPR products, only the MS portion was analyzed in this study.

The L2 algorithms were developed by the DPR Algorithm Development Team under the Joint Algorithm Team of JAXA and the National Aeronautics and Space Administration (NASA) (Kubota et al. 2014; Iguchi et al. 2018; Iguchi 2020).

The L2 algorithms provide the precipitation estimates used to produce three sets of outputs: KuPR-only products,

FIG. 1. A flowchart of in the DPR-L2 algorithms.

KaPR-only products, and dual-frequency products using both KuPR and KaPR data. The KuPR-L2 algorithm generates the KuPR-L2 product from the KuPR-L1 product, which includes Ku-band radar received power data. The KaPR-L2 algorithm generates the KaPR-L2 product from the KaPR-L1 product, which includes Ka-band radar received power data. The dual-frequency algorithm generates the dual-frequency product from the KuPR-L2 and KaPR-L2 products. Comparisons of KuPR-L2 (Ku), KaPR-L2 (Ka), and the dual-frequency (DF) products are shown in later sections using the DPR L2 algorithms for the GPM V06A product. The GPM V06A product was released in October 2018 (Iguchi and Meneghini 2018a,b,c) and uses the most current algorithm.

The DPR-L2 algorithms consist of several modules. Figure 1 shows a flowchart of the DPR-L2 algorithms. The preparation (PRE) module provides measured radar reflectivity factor (Z_m), apparent normalized radar cross section (NRCS) of surface (σ_m^0), precipitation–no-precipitation classification, and clutter mitigation (Kubota et al. 2016). The vertical profile (VER) module computes the path-integrated attenuation (PIA) due to nonprecipitation (NP) particles (piaNP), and generates a radar reflectivity factor corrected for the piaNP. This study focuses on the VER module, which will be further described in section 2d. The classification (CSF) module classifies precipitation types and brightband information based upon Awaka et al. (2016) and Le et al. (2016). The surface reference technique (SRT) module estimates the PIA for precipitation pixels (Meneghini et al. 2015). The solver (SLV) module numerically solves the radar equations and obtains DSD parameters and precipitation rates at each range bin (Seto et al. 2013, 2015, 2016; Seto and Iguchi 2015; Seto 2019; Seto et al. 2020, manuscript submitted to *J. Meteor. Soc. Japan*).

The SLV module in the single-frequency algorithms uses a combination of the Hitschfeld–Bordan attenuation correction method (HB method) and the SRT method, similar to the PR 2A25 algorithm (Iguchi et al. 2000, 2009). In the dual frequency, the SLV module uses a combination of the HB method, the dual-frequency SRT (DSRT) method (Meneghini et al. 2015) and an adjustment using KaPR's Z_m (Seto 2019) in the algorithm for the GPM V06A. The following relationship between precipitation rate R and volume-weighted mean drop size D_m (so-called, R – D_m relationship) is adopted in the current SLV module (Seto et al. 2016):

$$R = 0.401\varepsilon^{4.649}D_m^{6.131} \quad (\text{for “stratiform” precipitation}), \quad (1)$$

$$R = 1.370\varepsilon^{4.258}D_m^{5.420} \quad (\text{for “convective” precipitation}). \quad (2)$$

Here, “ ε ” is an adjustment factor. In the single-frequency algorithms, a priori probabilities of the ε are variable in time and space, while they are fixed in the dual-frequency algorithm. In the single-frequency algorithms, the SRT method is used to adjust the ε . In the dual frequency, the SLV module mainly uses Z_m of the KuPR and the DSRT and KaPR's Z_m are used to adjust the ε . A reliability of the SRT (or the DSRT) method is evaluated in terms of standard deviations of the σ_m^0 in the reference dataset and comparisons between the PIA due to the SRT method and the PIA due to the HB method. When the reliability is higher than a threshold, the SRT (or the DSRT) method adjusts the ε . Seto et al. (2020, manuscript submitted to *J. Meteor. Soc. Japan*) provides full descriptions of the SLV module.

The SLV module provides two type of surface precipitation rate, i.e., “precipRateNearSurface” and “precipRateESurface” in the DPR L2 products. The precipRateNearSurface is a precipitation rate at the lowest point free from mainlobe clutters. The precipRateESurface is a precipitation rate at the estimated surface. The DPR cannot observe near-surface precipitation rates due to surface clutter around 1.8 km altitude in the swath edge (Kubota et al. 2016). Therefore, the SLV module estimates a precipitation rate at the surface by assuming that the corrected radar reflectivity at the surface is identical to that at the lowest point free from mainlobe clutters (Seto et al. 2020, manuscript submitted to *J. Meteor. Soc. Japan*). This assumption may be problematic due to regional variations of low-level precipitation profiles as pointed by Hirose et al. (2012) using the TRMM PR data. Therefore, the VER module use the precipRateNearSurface in a calculation of the piaNP. On the other hand, the precipRateESurface is used in evaluations of experiments in sections 3 and 4, because the precipRateESurface is regarded as the end product of the algorithms.

b. NICAM

This study used 3.5-km-mesh global atmospheric simulation data calculated by the NICAM. The resolution of 3.5 km is comparable to that of the DPR footprint (5 km). The NICAM can be used as a GCRM that explicitly simulates convection and associated cloud-precipitation systems with a grid-resolved scale. See previous works (Hashino et al. 2013; Yamada et al. 2016; Nasuno et al. 2016) for the details of the simulation data.

The vertical grid had 40 levels up to the stratosphere. The simulation was initialized with the $0.5^\circ \times 0.5^\circ$ European Centre for Medium-Range Weather Forecasts (ECMWF) Year of Tropical Convection analysis (Waliser et al. 2012) at 0000 UTC 15 June 2008. Data used in this study were taken at 3-h intervals during the 9 days from 1200 UTC 16 June to 0900 UTC 25 June 2008. The cloud microphysics scheme was a single-moment bulk microphysical parameterization, called the NICAM Single-Moment Water 6 (NSW6) (Tomita 2008).

The advantage of the current NICAM simulation data is that they have already been analyzed in several papers (Hashino et al. 2013, 2016; Matsui et al. 2016; Yamada et al. 2016; Nasuno et al. 2016; Roh et al. 2017). This enables total understanding of the simulation data (including biases) and appropriate interpretations of the results in developing the satellite data algorithms. In comparisons of eight GCRMs with a grid spacing of 5 km or less, Stevens et al. (2019) demonstrated that horizontal distributions of cloud simulations captured the patterning of large-scale circulation features. However, it was found that cloud profiles were very different among the GCRMs (Roh et al. 2020, manuscript submitted to *J. Meteor. Soc. Japan*), probably because of differences in details of cloud microphysics schemes and dynamical cores. Therefore, the model results whose clouds are evaluated in existing observations are ideal for the use of the algorithm development of this study. The current NICAM simulation data were evaluated against satellite data for the cloud microphysics in previous works (Hashino et al. 2013, 2016; Matsui et al. 2016; Roh et al. 2017). They were used also in meteorological studies of tropical cyclones (Yamada et al. 2016; Nasuno et al. 2016). Yamada et al. (2016) showed a reliable track of the Typhoon Fengshen (2008) using the current simulation data, while it was poorly predicted by an operational numerical weather prediction (NWP) model. They suggested the importance of reproducing inner-core updrafts for better track prediction of a typhoon in an environment with strong vertical shear. Figure 2 shows global distribution of the CLWP at 0000 UTC 20 June 2008, analyzed in Yamada et al. (2016). Figure 2 demonstrates the NICAM data simulated various cloud systems in a global scale. Figure 3a shows an enlarged figure of the CLWP for the Typhoon Fengshen (2008). The CLWP distribution related to eyewall clouds and spiral rainbands of the Typhoon Fengshen (2008) was clearly found in Fig. 3a.

Note that the current study is focused upon the cloud data only in precipitating clouds. Figure 4 shows zonal mean values of the CLWP averaged over nine days. To reduce seasonal dependencies, the CLWP values were averaged by absolute values of the latitude. Figure 4 compares values averaged for all cases and cases with the surface precipitation can be observed by the DPR. As noted in section 2a, the DPR cannot observe near-surface precipitation rates due to surface clutter. A minimum detectable precipitation rate is 0.2 mm h^{-1} in design specifications of a high-sensitivity mode in the KaPR (Kojima et al. 2012). Therefore, a precipitation rate at 1.9 km altitude of the NICAM $>0.2 \text{ mm h}^{-1}$ was used here as a criterion for the DPR-observable surface precipitation. The CLWP tended to be more than 10 times larger for cases with the DPR-observable surface precipitation than those in all

FIG. 2. Horizontal distribution of cloud liquid water path (CLWP) of 3.5-km-mesh NICAM simulation data at 1200 UTC 19 Jun 2008. Rectangle surrounded by blue lines shows a domain shown in Fig. 3.

cases over the tropics. The CLWP values with the DPR-observable surface precipitation were larger over the tropics than those over the higher latitudes. Figure 5 shows a histogram of occurrences for the CLWP comparing all cases and cases with the DPR-observable surface precipitation. The two lines were almost the same when the CLWP was more than

500 g m^{-2} . Thus, the histogram indicated larger CLWP values were found in the cases with the DPR-observable surface precipitation. To investigate an advantage of using 3.5-km-mesh data, representation of convection was compared between the original mesh data and coarser mesh data ($0.5^\circ \times 0.5^\circ$ latitude–longitude

FIG. 3. Horizontal distribution of CLWP for Typhoon Fengshen (2008) at 1200 UTC 19 Jun 2008 in (a) 3.5-km-mesh data, and (b) $0.5^\circ \times 0.5^\circ$ latitude–longitude gridded data.

FIG. 4. Zonal mean values of CLWP. Open circles show values averaged for all cases, and solid circles show values averaged for cases with the surface precipitation can be observed by the DPR. Horizontal axis denotes absolute values of latitudes. Vertical axis denotes CLWP (g m^{-2}).

grid, Fig. 3b) around the Typhoon Fengshen (2008). Even with the same simulation data, the structure of the typhoon was unclear with the $0.5^\circ \times 0.5^\circ$ grid. Peak values of the CLWP in the 3.5-km-mesh data were largely decreased in the $0.5^\circ \times 0.5^\circ$ grid.

We further examined the dependence of cloud representation on the data mesh size using the same simulation outputs (not the resolution dependence of simulation result itself, which is beyond the scope of this study). Figure 6 shows probability density function (PDF) of CLWP by 4 types of resolutions, i.e., 3.5-km-mesh data, $0.1^\circ \times 0.1^\circ$, $0.25^\circ \times 0.25^\circ$, and $0.5^\circ \times 0.5^\circ$ latitude–longitude gridded data, with the NICAM data for 9 days. Figure 6 clearly shows a relationship where PDF values with large values of the CLWP decrease with coarsening the resolutions. This suggests that variabilities of the cloud were very wide with the 3.5-km resolution and a nonuniformity should be considered in representation of the cloud. As noted in section 2a, the horizontal resolution of the DPR is 5 km. Thus, the use of the 3.5-km-mesh dataset is more useful than coarser mesh data by avoiding loss of information at the DPR resolution.

c. Construction of the CLWC database

Iguchi et al. (2009) estimated attenuation by CLWC based on the results of numerical simulation of storms with the CRM used in the TRMM 2A12 algorithm (Kummerow et al. 2001). Iguchi et al. (2009) noted significant differences between a convective storm and a stratiform storm, and they used a formulation of the attenuation by CLWC with the convective–stratiform classification, the surface rain rate, and the height above the ellipsoid (mean sea level).

Because the NICAM can provide global atmospheric simulation data, this study extends the ideas of Iguchi et al. (2009). The CLWC database in this study is a function of surface precipitation rate, precipitation type (convective or stratiform), temperature, latitude, and land surface type. This database was constructed using 3.5-km-mesh global simulation data over the nine days noted in section 2b. As noted in section 2a, the DPR cannot observe near-surface precipitation

FIG. 5. A histogram of occurrences for the CLWP comparing all cases (solid black), and cases with the surface precipitation can be observed by the DPR (dashed red).

rates due to surface clutter around 1.8-km altitude in the swath edge, and the `precipRateNearSurface` is used as the surface precipitation rate in the VER module to avoid the regional variations of low-level precipitation profiles. Therefore, the precipitation rate at a 1.9-km altitude in the NICAM simulation data is taken as the surface precipitation rate, in correspondence with the `precipRateNearSurface`. The surface precipitation includes both precipitating liquid and frozen hydrometeors. Vertical profiles of the CLWC were classified with reference to intensities of the surface precipitation rate with a dB scale of $10 \times \log_{10}$ (precipitation rate).

Convective and stratiform precipitation in the NICAM data are classified by the method of Nasuno and Satoh (2011), based on that of Churchill and Houze (1984) with modifications proposed by Tao et al. (1993). Figure 7 shows the relationship between the surface precipitation rate and the CLWP for convective (red) and stratiform (black) precipitation over the ocean using current NICAM simulation data. The 9-day period

FIG. 6. Probability density function (PDF) of CLWP by 3.5-km-mesh data (black), $0.1^\circ \times 0.1^\circ$ (red), $0.25^\circ \times 0.25^\circ$ (pink), and $0.5^\circ \times 0.5^\circ$ latitude–longitude gridded data.

FIG. 7. A relationship between the surface precipitation rate and the CLWP for convective (red) and stratiform (black) precipitation over the ocean. The average value (circles) and the standard deviation (1 sigma, bars) are shown for intensities of the surface precipitation rate. Horizontal axis denotes dBR scale of the surface precipitation rate, i.e., $10 \times \log_{10}$ (precipitation rate). Vertical axis denotes CLWP (g m^{-2}).

described in section 2b was analyzed here. The CLWP tended to be larger in convective precipitation than in stratiform precipitation, and the CLWP depended on the intensity of the surface precipitation rate. This confirms the precipitation classification (convective or stratiform) in the NICAM data is effective to classify the CLWP. Note that Fig. 7 also shows standard deviations of CLWP, and they have large amplitudes. These variabilities can be associated with the uncertainties in the CLWC estimate and will be studied in section 3.

To reduce seasonal dependencies, the CLWC profiles were classified by absolute values of the latitude with 10° boxes. As shown in Fig. 4 for the cases with the DPR-observable surface precipitation, averages by the absolute values of the latitude provided larger values of the CLWP over the tropics, and smaller values over the higher latitudes. This suggests that averages by the absolute values of the latitude are effective to reduce seasonal variabilities and produce the CLWC database in a quasi-climatological condition.

The profiles were also sorted by temperature because the CLWC can depend upon temperature profiles. Sorting by temperature has also been done for evaluations of cloud microphysics in the NICAM (Hashino et al. 2013). In addition, the CLWC data depended on land surface type (sea or land). Matsui et al. (2016) studied land–ocean contrast of the current NICAM simulation data. Differences of surface elevation over land were not considered here. After these classifications and sorting, averages of the CLWC were used as the database. Standard deviations of the CLWC will be used in section 3 for an experimental purpose.

Figures 8 and 9 show examples of CLWC vertical profiles in over-ocean precipitation. CLWC tended to increase when the surface precipitation rate increases for all latitudes. For convective precipitation (Fig. 8), clear peaks were found around 10° – 15°C with small surface precipitation rates on average in

the 0° – 10° latitudinal range. This can be associated with shallow precipitation. In large surface precipitation rates, peaks were around the freezing level (FL) defined by the NICAM, which can be related to deep precipitation. In contrast, all peaks were found around the FL in high latitudes. For stratiform precipitation, CLWC was much smaller than that for convective precipitation.

Thus, a CLWC value is assumed using the database with inputs of surface precipitation rate, precipitation type (convective or stratiform), temperature, latitude, and land surface type. The CLWC database described in this study was used in the DPR algorithms for the GPM V04A which was released in March 2016 and later versions.

d. Calculation of the attenuation by CLWC in the algorithms

The database described in section 2c is used for the CLWC assumption in the VER module of the DPR L2 algorithms. The VER module computes the piaNP as noted in section 2a. In this study, water vapor (WV), molecular oxygen (O_2), and the CLWC are included in the NP calculation of piaNP. An attenuation due to cloud ice is assumed to be negligibly small for Ku and Ka bands in the algorithms. The VER module also generates a radar reflectivity factor and a NRCS corrected for the piaNP. In GPM DPR processing, the VER module takes atmospheric data from the Japan Meteorological Agency (JMA) [specifically JMA Global Analysis (GANAL) and JMA's forecast (FCST) data] as ancillary environmental data (ENV) and interpolates values of the environmental parameters in the radar range bin. The resolution of the JMA data is $0.5^\circ \times 0.5^\circ$ latitude–longitude. Based upon an interpolation technique with the JMA data, the VER module provides pressure, temperature, water vapor, and cloud liquid water for each radar range bin.

Figure 10 is a flowchart of the VER module. In the single-frequency algorithms for the Ku/Ka L2, the processing is repeated once to obtain a reliable attenuation correction to the radar reflectivity, as shown in Fig. 1. In the first step of Ku/Ka-L2 processing, the piaNP is calculated from the atmospheric parameters derived from JMA data. Waters (1976) and Rosenkranz (1975) methods are used in the PIA calculation for WV and O_2 , respectively. In precipitation pixels, the PIA due to WV is calculated with the relative humidity of 90% when the JMA data give a value less than 90%. When the DPR detects precipitation, localized high relative humidity can be expected there. JMA data have a $0.5^\circ \times 0.5^\circ$ latitude–longitude grid and a much coarser resolution than the DPR resolution (5 km). Therefore, a correction method of the relative humidity is applied by setting it to 90% in the algorithm when precipitation is detected. A similar correction was made for the PR 2A25 algorithm (Iguchi et al. 2009).

In the first step, the PIA due to the CLWC (PIA_{CLWC}) is calculated from JMA data assuming Rayleigh scattering. The piaNP values using the JMA data are referred to as “piaNP_{ENV}.” At the end of the first step, the algorithms provide initial results of precipitation type from the CSF module and surface precipitation rates from the SLV module. The precipRateNearSurface is used as the surface precipitation rate in the VER module.

FIG. 8. CLWC vertical profiles in over-ocean convective precipitation averaged over the (a) 0° – 10° , (b) 20° – 30° , and (c) 40° – 50° latitude ranges. The profiles are classified in dBZ scale of the surface precipitation rate which is denoted by colors (warmer colors show stronger surface precipitation rates). Horizontal axis denotes CLWC (mg m^{-3}). Vertical axis denotes temperature ($^{\circ}\text{C}$).

In the second step, the PIA_{CLWC} is calculated for Rayleigh scattering using the CLWC value assumed from the NICAM database with inputs of the temperature profiles and the initial results when precipitation is detected. For cloud particles, the Rayleigh scattering approximation holds because wavelengths of Ku and Ka bands are much longer than the particle size. The Rayleigh scattering was calculated with Eqs. (1.52) and (1.59) in [Bringi and Chandrasekar \(2001\)](#) with complex refractive indices of water ([Ray 1972](#)) at 10°C for Ku and Ka bands. The result of the second step is used to calculate the final product in Ku/Ka-L2 processing.

In the dual-frequency processing, the attenuation by CLWC is calculated using the database and precipitation estimates from the Ku/Ka-L2 products. When both Ku and Ka detect precipitation, geolocation information and precipitation estimates of Ku are used to calculate the piaNP .

[Figure 11](#) shows a case study of a precipitation system over the northeast Africa at 0100 UTC 1 September 2017, processed by the Ka-L2 algorithm. In the case study, values of PIA_{CLWC} at the surface by the JMA data ($\text{PIA}_{\text{ENV-CLWCsfc}}$) were very small ([Fig. 11b](#)), and a pattern of the $\text{PIA}_{\text{ENV-CLWCsfc}}$ was not

similar to that of the surface precipitation ([Fig. 11a](#)). This can be due to limitations of cloud representations in the operational NWP model. On the other hand, [Fig. 11c](#) shows a horizontal distribution of the PIA_{CLWC} at the surface by the estimates from the CLWC database ($\text{PIA}_{\text{CLWCsfc}}$) and a pattern of the $\text{PIA}_{\text{CLWCsfc}}$ was similar to that of the surface precipitation. As demonstrated in [Fig. 11](#), the $\text{PIA}_{\text{CLWCsfc}}$ is provided only in pixels classified as “precipitation” by the PRE module, and $\text{piaNP}_{\text{ENV}}$ is the only information in the nonprecipitation pixels.

[Figure 12](#) shows scatterplots between the $\text{PIA}_{\text{ENV-CLWCsfc}}$ and the $\text{PIA}_{\text{CLWCsfc}}$ in the GPM orbit number: 19935. For convective precipitation ([Fig. 12a](#)), a variability of the $\text{PIA}_{\text{CLWCsfc}}$, ranging from 0 to 1.5 dB, is much larger than that of the $\text{PIA}_{\text{ENV-CLWCsfc}}$. [Figure 6](#) showed smaller PDF values of the large CLWP values with the resolution of $0.5^{\circ} \times 0.5^{\circ}$ latitude–longitude used in the JMA data than in the 3.5-km-mesh resolution. Therefore, larger variability of the $\text{PIA}_{\text{CLWCsfc}}$ than by the $\text{PIA}_{\text{ENV-CLWCsfc}}$ in convective precipitation is consistent with results of [Fig. 6](#). In contrast, the $\text{PIA}_{\text{CLWCsfc}}$ was less than 0.5 dB in stratiform precipitation ([Fig. 12b](#)).

FIG. 9. As in Fig. 8, but for the over-ocean stratiform precipitation.

This corresponded to the results of Fig. 7, which showed the CLWP tended to be larger in convective precipitation than in stratiform precipitation. In both convective and stratiform precipitation, there were moderate cases of the $\text{PIA}_{\text{CLWCsfc}}$ with values more than 0 dB while the $\text{PIA}_{\text{ENV-CLWCsfc}}$ were equal to 0 dB. This confirms the estimates from the CLWC database corrected the PIA_{CLWC} in pixels where the cloud representations of the NWP model were poor, like Fig. 11. These verified efficiencies of the method developed using the CLWC database ($\text{PIA}_{\text{CLWCsfc}}$) with reference to the JMA data ($\text{PIA}_{\text{ENV-CLWCsfc}}$).

3. Evaluations of the CLWC assumption using the DPR-L2 algorithms

a. Experimental design

In evaluating the CLWC assumption for precipitation retrievals of the DPR observations, we conducted experiments using the DPR L2 algorithms for the GPM V06A product. Table 1 summarizes the experiments described in this study. Results by the algorithms in the GPM V06A is referred to as “DEF.” Comparisons of precipitation retrieval results in the experiments with reference to the DEF can provide impacts of

the assumption of the CLWC using the current database. Results were compared among the Ku, the Ka, and the DF algorithms using estimates over the interior MS portion of the swath. Surface precipitation rates of the DPR data were calculated for a period of one month (from 1 to 30 September 2017). Here, a precipitation rate at the estimated surface, referred to as “precipRateESurface” in the DPR L2 products, was used as the surface precipitation rate. Figure 13 shows monthly accumulation of surface precipitation by the DF algorithm during September 2017. Pixels of the DPR are assigned to $5.0^\circ \times 5.0^\circ$ latitude–longitude boxes in Fig. 13. Surface precipitation data with $5.0^\circ \times 5.0^\circ$ resolution were evaluated in section 3. Figure 14 shows the zonally averaged monthly accumulation of surface precipitation by the Ku, the Ka, and the DF algorithm in the GPM V06A (DEF) for September 2017. Relatively large underestimates were found in the Ka, while the differences were small in the Ku and the DF, except for the deep tropics. Seto (2019) validated the DPR V06A products using rain gauge data from the JMA and showed that the surface precipitation had been underestimated in the Ka. Seto (2019) suggests that the Ka was underestimated because of the unavailability of the SRT technique in larger PIA cases with disappearances of the

FIG. 10. A flowchart of the VER module in the DPR algorithms. Shades show functions of the VER module.

surface echoes. K. Kanemaru (NICT, 2020, personal communication) pointed out extreme large precipitation rates in the DF caused the differences between the Ku and the DF over the deep tropics in the GPM V06A products.

b. Impact of the CLWC assumption in precipitation retrievals

Surface precipitation rates of the DPR data when CLWC was set to 0 mg m^{-3} were calculated and referred to as “ZER” experiment. Figure 15 shows global maps of mean absolute difference (MAD) of surface precipitation rates between the DEF and the ZER. Here, $\text{MAD} = |P_{\text{DEF}} - P_{\text{EXP}}|$ with surface precipitation from the experiments (P_{EXP}) and that by the DEF (P_{DEF}), calculated in the DPR pixels. Overall, the MAD values were larger in the tropics than in the high latitudes (similar to the precipitation averages shown in Fig. 13); they were smallest in the Ku (Fig. 15a) and largest in the Ka (Fig. 15b). Because the attenuation by CLWC is larger in the Ka than in the Ku, this result can be expected. However, note that the impact of CLWC was larger in the DF algorithm than in the Ku algorithm and smaller than in the Ka algorithm.

Figure 16 shows the normalized mean absolute difference (NMAD) of surface precipitation rates between the DEF and the ZER. Here, NMAD was defined as the monthly zonal mean of MAD, divided by the monthly zonal mean precipitation amount of the DEF; that is, $\text{NMAD} = |P_{\text{DEF}} - P_{\text{EXP}}|/P_{\text{DEF}} (\%)$ with the P_{EXP} and the P_{DEF} . As shown in Fig. 14, the underestimations of the Ka were clear, and therefore, the normalization was used as a measure of the impact in the algorithms. The NMAD tended to be larger in the tropics, and they were

smallest in the Ku and largest in the Ka. Table 2 provides NMAD values averaged for all surfaces of global (70°S – 70°N) or tropical (15°S – 15°N) domains and confirmed larger NMAD values averaged in the tropical domain than in the global domain. Thus, the impacts of the CLWC assumptions to the surface precipitation estimates were larger in the Ka and smaller in the Ku, and larger in the tropics than in high latitudes.

When the CLWC profiles in the NICAM were sorted and classified, there were multiple profiles in the database. In the DEF, CLWC amount was assumed from an average of CLWC database. However, the variability of the CLWC profiles can lead to uncertainties of the database. To quantities these, an experiment with CLWC amount assumed from an average plus a standard deviation of CLWC database is conducted as “PER.” Figure 17 shows the NMAD of surface precipitation rates between the PER and the DEF. The NMAD values tended to be larger in the tropics, and they were smallest in the Ku and largest in the Ka. They were comparable to the values between the DEF and the ZER, shown in Fig. 16. This suggests the uncertainties of the CLWC database can provide effects in the precipitation retrievals, in particular, for the Ka, and improvements of the classification method of the CLWC is one of future tasks.

4. Retrieval processes affected by the CLWC assumption

Section 3 evaluated the impact of the CLWC assumption on precipitation retrievals using the differences between the DEF and the ZER. In the algorithms, the following factors can affect the precipitation estimate by the CLWC assumption.

FIG. 11. A case study of a precipitation system over northeast Africa at 0100 UTC 1 Sep 2017 (in GPM orbit number 19935), processed by the Ka-L2 algorithm. (a) Surface precipitation, (b) PIA_{CLWC} by the JMA data ($\text{PIA}_{\text{ENV-CLWCsfc}}$), and (c) PIA_{CLWC} by the estimates from the CLWC database ($\text{PIA}_{\text{CLWCsfc}}$).

a. Correction of radar reflectivity by the piaNP

In the VER module, the measured radar reflectivity, Z_m , is corrected considering the PIA due to the nonprecipitation (WV, O_2 , and CLWC) in each range bin ($\text{piaNP}_{\text{range}}$) as follows:

$$Z_{\text{NPC}} = Z_m + \text{piaNP}_{\text{range}} = Z_m + \text{PIA}_{\text{CLWCrange}} + \text{PIA}_{\text{WVO2range}}. \quad (3)$$

Here, Z_{NPC} is the radar reflectivity corrected by the $\text{piaNP}_{\text{range}}$. The $\text{piaNP}_{\text{range}}$ consists of the PIA due the CLWC ($\text{PIA}_{\text{CLWCrange}}$) and the PIA due to the WV and O_2 ($\text{PIA}_{\text{WVO2range}}$). When the $\text{PIA}_{\text{CLWCrange}}$ is increased by the assumed CLWC amount, Z_{NPC} increases. This can lead to increases in estimated precipitation rates.

b. The estimation of the PIA due to rain with consideration of the piaNP

In the SLV module, the PIA due to rain (PIA_{rain}) is used for the precipitation retrievals defined as follows:

$$\begin{aligned} \text{PIA}_{\text{rain}} &= \text{PIA}_{\text{SRT}} - (\text{piaNP}_{\text{sfc}} - \text{piaNP}_{\text{ENVsfc}}) \\ &= \text{PIA}_{\text{SRT}} - \{(\text{PIA}_{\text{CLWCsfc}} + \text{PIA}_{\text{WVO2sfc}}) - \text{piaNP}_{\text{ENVsfc}}\}, \end{aligned} \quad (4)$$

where PIA_{SRT} is the value of the PIA provided by the SRT module based upon the apparent NRCS of surface σ_m^0 ; $\text{piaNP}_{\text{sfc}}$ is the PIA due to the nonprecipitation at the surface, consisting of the PIA by the CLWC ($\text{PIA}_{\text{CLWCsfc}}$) and the PIA by the WV and O_2 ($\text{PIA}_{\text{WVO2sfc}}$); and $\text{piaNP}_{\text{ENVsfc}}$ is the PIA by the NP at the surface using the JMA data. When the $\text{PIA}_{\text{CLWCsfc}}$ is increased by the CLWC assumption, PIA_{rain} decreases. This can lead to decreases in the attenuation corrections and in estimated precipitation rates. Note that differences between $\text{piaNP}_{\text{sfc}}$ and $\text{piaNP}_{\text{ENVsfc}}$ were regarded here as differences of the piaNP between precipitation pixels and nonprecipitation pixels. The SRT method provides the PIA estimates with the rain-free reference. The rain-free reference may include cloud-related influences, and $\text{piaNP}_{\text{ENVsfc}}$ was used as a representative of them in the algorithm for V06A.

To quantitatively verify these factors, we conducted the experiments corresponding to factor *A* (ZNP) and corresponding to factor *B* (PSV). In the ZNP experiment, radar reflectivity, Z_m , is not corrected by the $\text{PIA}_{\text{CLWCrange}}$ by setting it to 0 dB in Eq. (3). On the other hand, the $\text{PIA}_{\text{CLWCsfc}}$ is used to correct the PIA_{rain} in Eq. (4). In the PSV experiment, the PIA_{rain} is not corrected by the $\text{PIA}_{\text{CLWCsfc}}$ by setting it to 0 dB

FIG. 12. Scatterplots between the $PIA_{ENV-CLWCsfc}$ and the $PIA_{CLWCsfc}$ in the GPM orbit number 19935 for (a) convective and (b) stratiform precipitation.

in Eq. (4) while the Z_m is corrected by the $PIA_{CLWC_{range}}$ in Eq. (3). Surface precipitation data with $5.0^\circ \times 5.0^\circ$ resolution were evaluated also in section 4. Figure 18 shows the normalized mean difference (NMD) of surface precipitation rates between the DEF and the ZNP, and between the DEF and the PSV. Here, NMD was defined as the monthly zonal mean of the mean difference values, divided by the monthly zonal mean precipitation amount of the DEF, that is, $NMD = (P_{DEF} - P_{EXP})/P_{DEF}$ (%). In Fig. 18a for factor A , the NMD values were positive for all products. This confirmed that the attenuation correction in Z_m by CLWC increases the surface precipitation. The NMD values for Ka were larger than that for Ku and DF. The intensities of NMD were higher in the mid-high latitudes, while they were lower in the tropics. As noted in section 2a, the DF algorithm mainly uses Z_m of the KuPR (Seto et al. 2016; Seto 2019; Seto et al. 2020, manuscript submitted to *J. Meteor. Soc. Japan*). As a result, effects of the cloud assumption in the DF were comparable to those in the Ku.

In Fig. 18b for factor B , the NMD values were negative for all products. This confirmed the estimation of the PIA_{rain} with consideration of the PIA by CLWC decreases the surface precipitation. The intensities of the NMD for the Ka and the DF were larger than that for the Ku and peaked in the tropics. As described in section 2a, the adjustment of the ε using the PIA_{rain} is larger in the SLV module when the reliability of the SRT method is higher. Higher precipitation rates are more frequently observed over the tropics than over the higher latitudes, and the SRT method is more reliable in

higher precipitation rates. Thus, differences between DEF and PSV were larger over the tropics. On the other hand, the SRT method is not reliable for weak precipitation in the Ka, and precipitation is estimated based upon the HB method using the a priori probability of the ε . This precipitation estimation method is directly connected to intensities of Z_{NPC} related to factor A , and differences of the Ka between DEF and ZNP

TABLE 1. A summary of the experiments using the DPR L2 algorithms of the GPM V06A products in this study.

Name	Contents
DEF	Results in GPM V06A algorithms: CLWC amount assumed from an average of CLWC database
ZER	CLWC amount assumed to be 0 mg m^{-3}
PER	CLWC amount assumed from an average plus a standard deviation of CLWC database
ZNP	CLWC amount assumed from an average of CLWC database Radar reflectivity not corrected by PIA due to the CLWC PIA due to the CLWC used in estimating the PIA due to rain
PSV	CLWC amount assumed from an average of CLWC database Radar reflectivity corrected by PIA due to the CLWC PIA due to the CLWC not used in estimating the PIA due to rain

FIG. 13. Monthly accumulation of surface precipitation (mm month^{-1}) by the dual-frequency (DF) algorithm for the GPM V06A (DEF) during September 2017. The horizontal resolution is $5.0^\circ \times 5.0^\circ$ latitude-longitude.

were larger over the higher latitudes where weak precipitation is frequently observed.

Note that the effects of factor *A* to increase precipitation are offset by the effects of factor *B* to decrease precipitation. While the NMAD is helpful in understanding the impact of the CLWC assumption, residual differences related to the CLWC assumption can be smaller than the NMAD, because the precipitation amount results in summing effects between factor *A* and factor *B*. Figure 19 shows the NMD between the DEF and the ZER (analyzed in section 3b) and combines the offset between factors *A* and *B*. Table 3 summarizes the NMD values of surface precipitation rates between the DEF and the ZER for the global or tropical domains. Comparing Table 3 of the NMD and Table 2 of the NMAD confirmed the offsets between factor *A* and factor *B* reduced residual differences related to the CLWC assumption. Nevertheless, it should be emphasized that the effects of factor *B* to decrease precipitation were dominant because all values in the Table 3 show the negative sign. As precipitation intensity increases, the assumed amount of the CLWC also increases, as shown in Figs. 8 and 9, thereby increasing the impact on the precipitation estimation. This effect affects the precipitation estimation in the algorithm through the PIA_{rain} estimation.

5. Summary and discussion

While an attenuation due to cloud ice is negligibly small for Ku and Ka bands, attenuation by CLWC can be larger in the Ka band and estimating precipitation intensity with high accuracy from Ka-band observations can require developing a method to estimate the attenuation due to CLWC. This paper described the CLWC assumption for precipitation retrievals of GPM DPR observations. Furthermore, impacts of the CLWC assumption were evaluated by experiments using the DPR level-2 algorithm for GPM V06A products.

The CLWC database was constructed based on surface precipitation rate, precipitation type (convective or stratiform), temperature, latitude, and land surface type, using the

global 3.5-km-mesh NICAM simulation data. By comparing various resolutions (Fig. 6), it was confirmed that the use of the 3.5-km-mesh dataset was more useful than coarser mesh data by avoiding loss of information at the DPR resolution. The database was used for the calculation of the attenuation by CLWC in the VER module of the algorithm. A case study demonstrated the pattern of the PIA_{CLWC} by the estimates from the CLWC database was similar to that of the surface precipitation while the pattern of the PIA_{CLWC} by the JMA data was not (Fig. 11). Larger variability of PIA_{CLWC} by the database developed using the NICAM simulation data than by the JMA data was found in convective precipitation (Fig. 12).

By comparing the one-month experiment of CLWC with 0 mg m^{-3} (ZER), the impact of the current CLWC assumptions to surface precipitation estimates were quantified using the NMAD by 2.3% for the Ku, 9.9% for the Ka, and 6.5% for

FIG. 14. Zonally averaged monthly accumulation of surface precipitation (mm month^{-1}) by the Ku (crosses), Ka (open circles), and DF (solid circles) algorithms for the GPM V06A (DEF) during September 2017.

FIG. 16. Zonal mean values of normalized mean absolute difference (NMAD) of surface precipitation rates between the DEF and the ZER.

the DF algorithms in global averages (Table 2). The NMAD values were larger in the tropics than in the high latitudes.

In the algorithms, correction in the radar reflectivity by the piaNP (factor *A*) and consideration of the piaNP in estimating the PIA_{rain} (factor *B*) can affect the precipitation estimate made under the CLWC assumption. By the effects of the correction in the radar reflectivity by the piaNP, increases in the assumed CLWC leads to increases in the estimated precipitation rates. On the other hand, by the effects of the piaNP consideration in estimating the PIA_{rain} , increases of the assumed CLWC lead to decreases in the estimated precipitation rates. These were confirmed by experiments (ZNP and PSV). Because these effects offset each other, the residual differences related to the CLWC assumption (defined as the NMD) were smaller than the NMAD. However, this study emphasized the effects of factor *B* to decrease precipitation were dominant in the evaluations. As precipitation intensity increases, the assumed amount of the CLWC also increases, thereby increasing the impact on the precipitation estimation. This effect affects the precipitation estimation in the algorithm through the PIA_{rain} estimation.

In this study, the CLWC database was constructed by extending an idea put forth by Iguchi et al. (2009). However, there was considerable deviation in the CLWC data for the classification as demonstrated in Fig. 7. These variabilities can be related to uncertainties in the CLWC estimate, and also precipitation retrievals in the GPM DPR data. Actually, the NMAD values between the DEF and the PER (CLWC amount is estimated with an average plus a standard deviation of the database) were comparable to the values between the DEF and the ZER (CLWC amount is assumed to be 0). Adopting a more elaborate technique, such as an empirical orthogonal function (EOF) decomposition (Greco et al. 2016) and utilization of meteorological conditions (e.g., Shige and Kummerow 2016), will require future work.

In the GPM V06A algorithm, differences between $piaNP_{sfc}$ and $piaNP_{ENVsfc}$ were regarded as the differences of the piaNP between precipitation pixels and nonprecipitation pixels, because the $piaNP_{ENVsfc}$ was the only information in

TABLE 2. NMAD values (%) of surface precipitation rates between the DEF and the ZER for global (70°S–70°N) or tropical (15°S–15°N) domains.

Domain	Ku	Ka	DF
Global	2.3	9.9	6.5
Tropical	4.3	14.9	10.0

the nonprecipitation pixels. The resolution of the JMA data ($0.5^\circ \times 0.5^\circ$ latitude–longitude) is much coarser than that of the DPR footprint (5 km). Figure 12 showed that the differences of the PIA_{CLWC} between the JMA data and the database from the NICAM data were larger in convective precipitation, and that they can reflect the differences of the piaNP between precipitation pixels and nonprecipitation pixels to some extent. However, to estimate more accurate and consistent PIA_{rain} , the PIA_{CLWC} in no-precipitation conditions should be estimated using the database derived from the NICAM simulation data. Currently, a dependence upon the surface precipitation rate is a critical constraint and this cannot be established in the nonprecipitation conditions. Further efforts will be necessary to develop the database in the nonprecipitation conditions using the NICAM simulation data and this is regarded as one of future tasks.

Convective and stratiform precipitation in the NICAM data were classified by the method of Nasuno and Satoh (2011). A target of the Nasuno and Satoh (2011) was evaluating the NICAM with the TRMM data in the 10°N–10°S domain; classification in the other latitudes was beyond their scope. In this study, their method was also applied to the NICAM precipitation over all latitudes. Figure 7 confirmed that the precipitation classification (convective or stratiform) in the NICAM data was effective to classify the CLWP. However, because an improvement of the precipitation classification over the latitudes not observed by the TRMM in the DPR-L2 algorithm is in progress (Awaka et al. 2016), continuous efforts are necessary to develop the convective–stratiform classification method in the NICAM consistent with the DPR method.

FIG. 17. As in Fig. 16, but for the NMAD of surface precipitation rates between the DEF and the PER.

FIG. 18. Normalized mean difference (NMD) of surface precipitation rates (a) between the DEF and the ZNP and (b) between the DEF and the PSV.

To reduce seasonal dependencies of 9-day data used in this study, the CLWC profiles in the NICAM simulation data were classified by the absolute values of the latitude. Averages by the absolute values of the latitude provided large values of the CLWP over the tropics, and smaller values over the higher latitudes, in the cases with the DPR-observable surface precipitation (Fig. 4). This suggests that averages by the absolute values of the latitude are effective to reduce seasonal variabilities and produce the CLWC database in a quasi-climatological condition. On the other hand, the database ignored some potentially significant differences in southern versus Northern Hemisphere CLWC properties. Noda et al. (2016) conducted 7-km-mesh global atmospheric simulation using the NICAM for a full year (1 June 2004–31 May 2005). While a full year or longer-term 3.5-km-mesh global atmospheric simulation is still challenging, utilizations of longer-term GCRM data are tasks remaining for the future, to reproduce seasonal variability of the CLWC.

Furthermore, the uncertainties related to the cloud microphysics in the NICAM simulation are important to better precipitation retrievals. As noted in section 2b, the current NICAM simulation data were evaluated against satellite data used in previous works (Hashino et al. 2013, 2016; Matsui et al. 2016). Using the TRMM data and the Joint Simulator for Satellite Sensors (Joint Simulator), Matsui et al. (2016)

FIG. 19. As in Fig. 18, but for the NMD of surface precipitation rates between the DEF and the ZER.

indicated that the NICAM simulations could represent convective land–ocean contrasts in warm precipitation to some extent, while they overestimated shallow warm precipitation over the tropics. In Hashino et al. (2013, 2016), the cloud microphysics of the current NICAM simulation data was evaluated by satellite data of *CloudSat* radar, *CALIPSO* lidar, and *Aqua* Clouds and the Earth's Radiant Energy System (CERES) data using the Joint Simulator. Hashino et al. (2013) suggested that the simulations had too low a cloud water content and too efficient a conversion of cloud water to rain.

Such deficiencies in the capability of the cloud microphysics of the NICAM simulation data may introduce uncertainties in the DPR algorithms. The cloud microphysics of the NICAM has been improved, for example, in Roh et al. (2017) which describes an improved single-moment bulk microphysics evaluated using the TRMM and a satellite simulator, and Seiki et al. (2015) which describes a double-moment bulk cloud microphysics scheme. Utilizations of simulation data using the improved cloud microphysics are tasks remaining for the future and could possibly be incorporated into future retrieval algorithms.

The CLWC database described in this study was used also in the TRMM PR algorithm for the TRMM V8 (GPM PR V06A) which was released in July 2018 (TRMM 2018). While the current CLWC database has been developed for the GPM DPR and the TRMM PR algorithms, refining the CLWC assumptions is an important task in improving precipitation estimates for the CPR on board the *CloudSat* (Stephens et al. 2002) and the EarthCARE (Illingworth et al. 2015). Applications of the CLWC database to spaceborne W-band radar will be an interesting topic for the future.

TABLE 3. NMD values (%) of surface precipitation rates between the DEF and the ZER for global (70°S–70°N) or tropical (15°S–15°N).

Domain	Ku	Ka	DF
Global	−0.9	−3.3	−5.3
Tropical	−2.7	−7.6	−8.8

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