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Microphysical properties of various precipitation systems worldwide classified via objective methods based on dual-frequency precipitation radar observations

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Abstract. Microphysical properties play crucial roles in physical processes related to the development of precipitation. In this study, Global Precipitation Measurement (GPM) dual-frequency precipitation radar (DPR) data were processed to demonstrate the microphysical properties of different precipitation systems (PSs) that are objectively classified with the k-means clustering algorithm. Four types of regular/non-extreme PS (high-latitude shallow PS, subtropical shallow PS, moderate PS, deep PS) and four types of extreme PS (extreme deep PS, strong PS, extreme strong PS, and marine extreme PS) were recognized. These eight types of PS exhibit differences in spatial-temporal features and convection characteristics, such as storm height, rain intensity, and vertical structures. For example, with the highest radar echo top and the largest mean mass-weighted mean diameter (D_m), the extreme strong PS mainly locate over tropical continent, while the high-latitude shallow PS have the least precipitation rate and mean normalized intercept parameter (N_w) values. The relationships between convection features and microphysical properties also vary among the eight types of PSs. For extreme PS, maximum precipitation rate near the surface generally exceeds 100 mm h^{-1} and balanced breakup and coalescence processes play a dominant role compared with non-extreme PS. In contrary, the coalescence processes dominate near the surface in two types of shallow PS. These results highlight the diversity of global precipitation microphysics and emphasize the necessity of global studies to increase the understanding of precipitation processes.

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1. Introduction

The microphysical characteristics of precipitation provide crucial information for describing precipitation. The deficiency of precipitation microphysical parameterization schemes is a significant factor contributing to precipitation errors in weather and climate models (Snook and Xue, 2008). Accurately obtaining spatial and temporal distributions and variations in precipitation microphysical parameters is essential for understanding the physical processes of precipitation, increasing the accuracy of quantitative precipitation estimation (QPE), and evaluating microphysical parameterizations in models (Chen et al., 2011; Zhang et al., 2023). Currently, observations and characteristics of precipitation microphysics at the global scale remain lacking because of the limited number of observation approaches.

The drop size distribution (DSD) is a typical metric for depicting precipitation microphysics. DSD features can be derived from observations obtained via disdrometers, ground-based radar instruments, and space-based radar instruments. In radar instruments, the interaction of electromagnetic waves with hydrometeors is used to retrieve DSD parameters (Marzuki et al., 2023), whereas disdrometers measure raindrop counts to directly obtain DSDs at the surface. Disdrometers provide only point measurements at specific levels and cannot measure the vertical structure of DSDs. Moreover, disdrometers have not been deployed globally, especially over the ocean. Although ground-based radar instruments can measure the three-dimensional structure of precipitation, they can only be used in limited areas, and their observation accuracy is significantly affected by the terrain conditions within the observation area (Dai et al., 2020). In contrast, space-based radar instruments can provide the vertical structures of DSD parameters worldwide. This study focused on the microphysical characteristics of various precipitation systems (PSs) worldwide. Compared with other instruments, space-based radar instruments are the most suitable for researching global precipitation microphysics.

In 1997, the Tropical Rainfall Measuring Mission (TRMM) satellite was launched by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA). The precipitation radar (PR), which operates in the Ku-band (13.8 GHz), was carried by the TRMM (Iguchi et al., 2000). This marked the beginning of the observation of precipitation microphysics via space-based radar instruments. Notably, DSD parameters were retrieved from the radar reflectivity measured by the PR with the assumption that the DSD can be characterized by the diameter parameter itself (Iguchi et al., 2000). As a result, the DSDs obtained via retrieval exhibited large errors. In 2014, NASA and JAXA successfully launched the Global Precipitation Measurement (GPM) Core Observatory (GPM-CO). The GPM-CO carried the first spaceborne dual-frequency precipitation radar (DPR) system, operating in the Ku and Ka bands (13 and 35 GHz, respectively) (Skofronick-Jackson et al., 2017). The differential scattering during rainfall at these two frequencies is directly related to the size of raindrops (Gatlin et al., 2020). Via the use of this characteristic, D_m and N_w can be retrieved. The retrieved DSD parameters have been verified with ground-based observations and are better than those obtained via the TRMM PR algorithm (Sun et al., 2020). In addition, validation studies have confirmed the feasibility of using DPR observations for DSD parameter analysis (D'Adderio et al., 2018; Peinó et al., 2024). Peinó et al. (2024) used observational data from seven Parsivel disdrometers across different topographic zones in the western Mediterranean to validate GPM

DSD products. They reported that the GPM DPR products effectively captured the variations in DSDs observed under different rainfall intensities. Therefore, GPM DSD products have been widely employed to investigate the microphysical characteristics of precipitation in the literature (Wen et al., 2024, 2023) .

However, previous studies involving GPM DSD products have focused mainly on specific locations or weather systems. For example, Li et al. (2024) studied the vertical structure and DSD characteristics of different precipitation types during the rainy season over South China and reported that the precipitation type and intensity affect the DSD parameters. In their study, under the same precipitation intensity, shallow convective precipitation exhibited the smallest D_m and largest N_w values, whereas deep convective precipitation exhibited the opposite phenomenon. Additionally, regarding stratiform precipitation, for PR > 3.5 mm h^{-1}, D_m slightly increased, and in regard to shallow convective precipitation, D_m remained at approximately 1.3 mm for PR > 2 mm h^{-1}. Similarly, Wen et al. (2023) analyzed the seasonal variations in the vertical structure of precipitation microphysics in East China. They reported that the spatial distributions of D_m and N_w demonstrate obvious seasonal variations and that there are more small raindrops in convective precipitation in autumn and winter than during the other seasons. These studies revealed the variations in microphysical characteristics across different seasons and rainfall types. Additionally, regarding weather conditions, regional variations in the precipitation characteristics of tropical cyclones (TCs) have been investigated over the North Indian Ocean (Kumar et al., 2023). Research has revealed that the nature of microphysical processes largely influences the growth of droplets in convective and stratiform rain. Wu et al. (2022) investigated the DSD characteristics of record-breaking Typhoon In-Fa (2021). Their findings revealed significant internal and regional differences in the microphysical characteristics of typhoon precipitation. When different precipitation types during Typhoon In-Fa were compared, convective precipitation (N_w values ranging from 3.80 to 3.96 m^{-3} mm^{-1}) exhibited higher raindrop concentrations than did stratiform precipitation (N_w values ranging from 3.40 to 3.50 m^{-3} mm^{-1}). Additionally, convective precipitation during Typhoon In-Fa indicated a greater (lower) raindrop concentration than that during Typhoon Taiwan (Hainan), while the raindrop diameter was smaller than those during both Typhoons Taiwan and Hainan. These studies primarily focused on the microphysical process and structure of various weather conditions, which provided insight into the formation process of precipitation. At present, there are few studies on the microphysical characteristics of large-scale and global PSs. On the one hand, as mentioned above, the DSD is influenced by numerous factors, such as precipitation type and season. There may be multiple precipitation types and DSDs in one area. On the other hand, few DSD datasets covering the whole world are available. Dolan et al. (2018) used twelve disdrometer datasets across three latitudinal zones—high-latitude, midlatitude, and low-latitude zones—to analyze DSD spatial variability. They reported that the DSD varies with latitude. At low latitudes, moderate D_m values (1.5–2 mm) and large $\log10(N_w)$ values (> 4 m^{-3} mm^{-1}) dominated. At midlatitudes, high D_m values and small N_w values dominated. At high latitudes, low D_m and large N_w values prevailed. Although the dataset covered a wide range of precipitation regimes, it could not capture all rain regimes. Moreover, a regional DSD dataset cannot represent the DSD within a given latitudinal band because of the limitations of disdrometers. Hence, in this study, GPM DSD products were employed to investigate the microphysical characteristics of PSs at global scales.

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This study aimed to classify different PSs on the basis of DPR observations via machine learning and to analyze the microphysical characteristics of different types if PSs. The results could address regional DSD variability and increase our understanding of the microphysical processes of different types of PSs. This study is organized in four sections. Section 2 provides detailed descriptions of the GPM data and machine learning models applied in this study. The main results are presented in Section 3, and finally, a summary is given in Section 4.

2. Data and methods

2.1. Data

GPM observations cover the range from 65° S to 65° N (Hou et al., 2014; Tapiador et al., 2012). The GPM DPR operates in the Ka and Ku bands, with a spatial resolution of approximately 5 × 5 km^2. The scanning of DPR is cross-track and has three scan patterns: normal scanning (NS), matching scanning (MS), and high sensitivity scanning (HS) (Das et al., 2022). Since the scanning pattern of the Ka-band was changed in 2018 (Awaka et al., 2021), the GPM 2A DPR (version 7) products considered the changes in the Ka-band scan pattern with a more accurate precipitation estimation algorithm. The product formats in version 7 have been changed from the original three types to two types: FS and HS. The FS product exhibits a new format and is defined as a full-scan dual-frequency product with a 125-m distance resolution. Compared with previous algorithms, the FS mode makes it possible for the first time to process a full-scan band of approximately 245 km in dual-band mode (Awaka et al., 2021). Therefore, the FS type was adopted in this study.

In this study, five years (2018–2022) of 2A DPR products (version 7) were employed. The parameters used in this machine learning model include DSD parameters (D_m and N_w), near-surface precipitation rate (mm h^{-1}), attenuation-corrected radar reflectivity (dBZ), reflectivity near the surface (Z_{surf}), and typeprecip (stratiform and convective precipitation pixels are distinguished by the typeprecip parameter), and airTemperature (this parameter can be used to distinguish between snow and rain).

2.2. Precipitation system (PS)

This paper presents a method based on the connected domain principle for identifying PSs similar to those contained the widely used TRMM/GPM Precipitation Feature dataset (Liu et al., 2008, 2020). Similar to the Precipitation Feature dataset (Liu et al., 2008), neighboring precipitation pixels, with a minimum precipitation rate of 0.1 mm h^{-1}, are grouped into a PS. Each PS is required to have a minimum of four precipitation pixels.

The DPR can observe the three-dimensional structure of precipitation and DPR products include radar reflectivity parameters and retrieved DSD parameters from 0 to 22 km with a range resolution of 125 m, resulting in a total of 176 layers of data. Consequently, for each PS type, DSD and radar reflectivity parameters such as the maximum and average values of each layer were calculated. The average D_m and N_w profiles were used for each PS, and if the profiles of the maximum D_m and N_w values in each layer were involved, MAX-D_m and MAX-N_w, respectively, were used. Given the potential

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relationships of the convective intensity with microphysical parameters, Z_e in the product was employed to calculate the maximum 20/30/40 dBZ echo top height (MAXHT20/30/40) for each type of PS (Liu, 2011; Liu et al., 2020; Ni et al., 2019; Roy et al., 2020), the echo top height of the PS (H_{top}) (Arulraj and Barros, 2021), and other convective parameters. To characterize the conditions of the PS, several additional features were calculated, such as the maximum precipitation rate near the surface (the maximum precipitation rate of the precipitation pixels included in the PS) and the precipitation area (the number of precipitation pixels contained in the PS). Considering that the GPM satellite exhibits a higher observation frequency in high-latitude regions (approximately 2–3 times that at the equator), the original dataset is prone to oversampling in these areas, which can introduce bias. To construct a balanced dataset suitable for clustering analysis, this study implemented a homogenization for the sampling. Specifically, the satellite's observation frequency was calculated as a function of latitude, and sample size for each latitude was adjusted using the ratio of its frequency to that at the equator. Subsequently, precipitation systems were randomly selected from each latitude to ensure a consistent scaled sample size, thereby effectively addressing the issue of uneven sampling. Finally, a total of 8,924,307 PSs were obtained for subsequent analysis.

2.3. Methods

In this study, two distinct machine learning models, namely k-means clustering and principal component analysis (PCA) were used. Both models were trained and evaluated via the Python scikit-learn package. These models are briefly described below. The k-means algorithm is one of the most popular clustering algorithms among machine learning algorithms. It is one of the most popular unsupervised clustering algorithms due to its efficiency (Jain, 2010). The algorithm follows a three-step process. Initially, it aims to select initial cluster centers by randomly obtaining sample coordinates from the dataset and assigning each sample to its nearest cluster center. Next, it computes the mean of all sample points assigned to each previous cluster center to establish new cluster centers. Finally, the algorithm aims to evaluate the differences between the new and old cluster centers. If differences are present, the last two steps are repeated until the cluster centers stabilize and no longer shift (Jain, 2010).

PCA is a classical dimensionality reduction tool in machine learning (Gang and Bajwa, 2022). PCA is based on the linear combination of target features to construct the principal subspace, and the variance is then employed to measure the information content with the aim of identifying the linear subspace with the maximum variance (Marukatat, 2023). In summary, PCA aims to transform numerous pertinent features into a comparatively limited number of irrelevant ones, thereby retaining as much of the informational content of the original data as possible (Gang and Bajwa, 2022). Considering that there are 176 vertical layers of GPM DPR products, if all DSD data were used as input parameters, the clustering effect could be poor because of the high dimensionality. In this study, PCA was adopted to reduce the dimensionality of the data while striking a balance between information loss and the optimal number of parameters to be retained (Festa et al., 2023; Jolliffe and Cadima, 2016).

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In this study, the maximum precipitation rate near the surface, H_{top}, the precipitation area, the proportion of stratiform precipitation, the proportion of convective precipitation, the DSD parameters (D_m and N_w) and the maximum radar reflectivity parameter (Z_e) after dimensionality reduction via PCA were used as input parameters for the k-means clustering algorithm. These parameters were selected based on their critical role in comprehensively characterizing the features, structure, and microphysical processes of precipitation systems. Among them, the maximum surface precipitation rate and Z_e reflect the intensity of the precipitation process and its echo characteristics, while the precipitation area directly characterizes the spatial differences in both the vertical and horizontal distributions of the system. The H_{top} not only reveals the vertical distribution but also captures the top-level information of the precipitation cloud through the maximum reflectivity height. Introducing the proportions of stratiform and convective precipitation facilitates the differentiation of precipitation types generated by distinct mechanisms, thereby elucidating their evolution patterns and dynamic characteristics. Furthermore, the DSD parameters (D_m and N_w) effectively describe the size distribution of precipitation particles and their intrinsic physical processes, providing an essential basis for an in-depth understanding of precipitation microphysics. Collectively, constructing a multidimensional precipitation feature space with these parameters enhances the accuracy and robustness of the clustering analysis.

The quality of clustering was evaluated by analyzing different clustering structures derived from the same dataset. The most commonly employed performance metrics, such as the sum of squared errors (SSE), Davis Bouldin (DB) index, Calinski-Harabasz (CH) Score (El Khattabi et al., 2024) and silhouette index, can be utilized to assess the effectiveness and quality of clustering algorithms (Ay et al., 2023). In this case, the DB index was calculated by computing the average sum of the intraclass distances between any two clusters divided by the distance between the centers of those two clusters and obtaining the maximum value. The DB index can manage clusters of different sizes and densities with a high degree of robustness to noise and outliers.

The DB index is calculated by computing the average sum of intraclass distances between clusters, divided by the distance between their respective centers, with the final value determined by the maximum across all clusters. A lower DB index indicates better clustering performance (Sowan et al., 2023). Additionally, the CH score, which assesses clustering compactness and separation, was also considered. Higher CH scores indicates better-defined clusters. Algorithms with clustering numbers ranging from 3 to 20 were executed, and the resulting change in the DB index and CH score was plotted (refer to Fig. S1 in the Supplementary Material). The results show that when K = 8, the DB index reaches its lowest value, while the CH score remains relatively high, indicating a well-balanced clustering structure. Therefore, the optimal number of clusters is eight. Combining all the features of the PSs described in Section 3, the Cluster 1-8 could be regarded as four non-extreme PS (high-latitude shallow PS, subtropical shallow PS, moderate PS, deep PS) and four extreme PS (extreme deep PS, strong PS, extreme strong PS, and marine extreme PS), which are listed here for the convenience of understanding the following context.

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3. Results and discussion

3.1. Global distributions

Table 1 shows the statistics of various parameters for the eight types of PS. There numbers include abundant information and verify the rationality of the objectively clustering algorithm. First, the numbers of the various types of PSs differed significantly. The two types of shallow PSs (high-latitude shallow PS and subtropical shallow PS) accounted for 81.44% of the total PS count. The proportions of deep and moderate PSs were 2.41% and 15.50%, respectively. The other four types of PS are regarded as extreme PS (extreme deep PS, strong PS, extreme strong PS, and marine extreme PS) because their ratios of the total PS are less than 1%, accounted for only 0.39%, 0.22%, 0.02%, and 0.01%, respectively. In the non-extreme PS, MAXHT20 is generally positively related to the precipitation rate (Table 1). However, in the extreme PS, the correlation between the extreme precipitation rate and MAXHT20 is not clear. For example, that the mean value of the maximum precipitation rate in marine extreme PS was the highest among the eight types of PSs, although its MAXHT20 was less than that in extreme strong PS and close to that in extreme deep PS. This result is consistent with other studies noting a weak link between the heaviest rainfall and the highest storm top (Hamada et al., 2015). Although the convective intensity of extreme deep PS is not significantly higher than that of deep PS, it exhibits a substantially larger precipitation area and maximum precipitation rate.

High-latitude shallow PS was most prevalent at midlatitudes and high latitudes, where snowfall and sleeting are more frequent than at low latitudes. Notably, high-latitude shallow PS were dominated by stratiform precipitation, with stratiform pixels accounting for 88.63%. Meanwhile, approximately 86.60% of the PS exhibited surface temperatures higher than 0 °C. A study confirmed that at high latitudes and in polar regions, more than 25% of precipitation falls as snow (Lerber et al., 2018). This is consistent with the observations from high-latitude shallow PS. Additionally, an analysis of high-latitude shallow PS by latitude revealed that with increasing latitude, the number of samples generally increased. Moreover, the number of PSs with echo top heights less than 2.5 km increased with latitude. During the winter season at 65°S, PSs with echo top heights below 2.5 km accounted for approximately 50% of the total PSs there. This is likely due to the influence of the low surface temperature and weak convection (refer to Fig. S2 in the Supplementary Material).

Subtropical shallow PS primarily occurred over the ocean where is dominated by the subtropical high, with a relatively limited degree of overlap with moderate PS and deep PS (Fig. 1). The mean MAXHT20 value in subtropical shallow PS was only 3.29 km, and the proportion of convective precipitation was the highest among all the types of PSs, exceeding 90%. Compared with those of the other PSs, subtropical shallow PS exhibited the smallest precipitation area. Moreover, it was rarely found over land. These results support the conclusion that subtropical shallow PS is associated with isolated shallow convection over the ocean, which has been the topic of interest in previous studies (Chen and Liu, 2016; Chudler et al., 2022; Houze Jr. et al., 2015).

The geographic distribution patterns of deep PS and moderate PS were approximately the same (Fig. 1). The number of occurrences in the maritime continent (MC), Indian Ocean, Atlantic Ocean, Amazon rainforests and Pacific Ocean were

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relatively high. There regions are generally influenced by the Intertropical Convergence Zone (ITCZ). Nevertheless, the deep PS has higher land percentage. The mean values of the maximum precipitation rates in moderate PS and deep PS were 6.21, 35.94 mm h^{-1}, respectively, whereas those of MAXHT20 were 7.03 and 11.89 km, respectively.

Strong PS, extreme deep PS, extreme strong PS, and marine extreme PS demonstrated low sample sizes. However, their precipitation areas are significantly larger than non-extreme PS (Table 1). The location of extreme deep PS is similar with moderate and deep PS, with larger values for most parameters. In the extreme strong PS, the proportion of land pixels reaches 81%, with significant concentrations in near-equatorial Africa, America, India, the southeastern U.S., and South America. The average maximum precipitation rate in extreme strong PS was 156.37 mm h^{-1}, and MAXHT40 reached 12.32 km, which is the highest among all the types of PSs. The high MAXHT40 value indicates strong updraft in the middle troposphere, which is favorable for hailstone formation. Therefore, the spatial distributions of hailstorms in extreme strong PS were very similar to those of hailstorms with large hailstones on the ground (Marra et al., 2017). Marine extreme PS was primarily situated in the near-equatorial marine region, with only 943 PSs and 90% is over the ocean. The mean maximum precipitation rate in marine extreme PS was 178.30 mm h^{-1}, ranking first among the eight types of PSs. Although the MAXHT20 value in marine extreme PS reached 12.81 km, the MAXHT40 value in marine extreme PS was approximately half of that in extreme strong PS, indicating low convection activity in the middle and upper levels. Oceanic extreme PS (extreme deep PS and marine extreme PS) with a high fraction of ocean pixels, exhibit a significantly larger precipitation coverage area than continental extreme PS (strong PS and extreme strong PS). This spatial distribution aligns with previous findings that the most extensive PS are predominantly located in oceanic regions. Furthermore, continental extreme PS display markedly stronger convective intensity. This disparity is largely attributable to the observation that the heaviest PS generally occur over tropical land, the Western Pacific warm pool, the North American Great Plains, and Argentina, whereas the most severe convective storms are predominantly observed over continental areas (Liu and Zipser, 2015).

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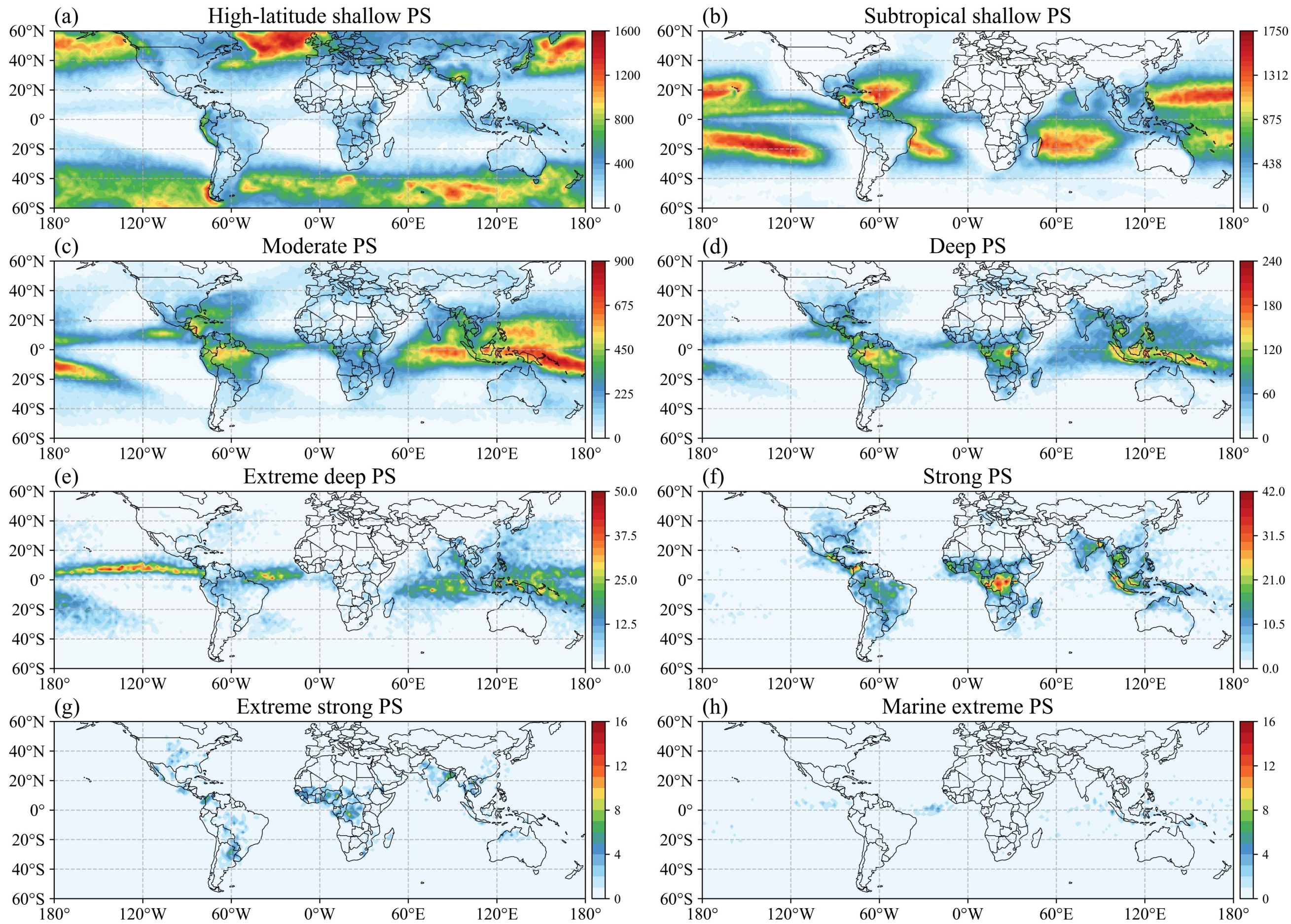

Figure 1. Spatial distributions (2° × 2°) of the PS counts from 2018 to 2022

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Table 1. Precipitation parameters for the different types of PSs. (* indicate that in high-latitude shallow PS and subtropical shallow PS, approximately 80% of the samples do not reach 40 dBZ. Therefore, the mean MAXHT40 for these samples is recorded as 0.)

	high-latitude shallow PS	subtropical shallow PS	Moderate PS	deep PS	extreme deep PS	strong PS	extreme strong PS	marine extreme PS
Mean MAXHT20 (km)	3.40	3.29	7.03	11.89	12.67	15.39	17.21	12.85
Mean MAXHT30 (km)	2.63	2.67	5.11	8.65	8.52	13.68	16.31	9.18
Mean MAXHT40 (km)	0.00*	0.00*	3.44	5.53	5.71	8.64	12.32	6.04
Stratiform percentages (%)	88.63	9.46	54.38	53.22	69.90	57.42	53.02	66.83
Convective percentages (%)	5.85	89.95	42.83	44.52	28.16	39.91	44.06	31.56
Land percentages (%)	21.61	6.97	27.96	42.31	15.61	65.37	80.98	10.45
Ocean percentages (%)	78.39	93.03	72.04	57.69	84.39	34.63	19.02	89.55
Mean precipitation (mm h^{-1})	1.60	2.35	6.21	35.94	156.67	135.46	156.37	178.30
precipitation Standard deviation (mm h^{-1})	1.63	1.92	8.89	50.44	98.44	106.95	103.50	98.61
Number of samples	4,184,547	3,083,077	1,383,261	215,611	34,982	19,790	2,096	943
Mean precipitation area (km^2)	610.57	239.23	2761.46	7009.37	37076.93	18485.91	22521.51	36044.11
>273.15 K frequency (%)	86.60	99.16	99.83	99.97	99.97	99.99	99.99	100.00
2.5 km Mean MAX-log10(N_w) [m^{-3} mm^{-1}]	3.47	3.70	4.06	4.49	5.20	4.72	4.88	6.07
2.5 km Mean MAX-D_m [mm]	1.03	1.17	2.26	2.82	2.71	3.04	3.11	2.61
2.5 km Mean log10(N_w) [m^{-3} mm^{-1}]	3.23	3.45	3.36	3.39	3.83	3.36	3.35	4.45
2.5 km Mean D_m [mm]	0.85	0.89	1.36	1.50	1.30	1.61	1.71	1.32

3.2. Global distributions of microphysical features

Fig. 2 and Fig. 3 show the global distributions of the microphysical parameters for the eight types of PSs. To avoid the influence of ground clutter, in each PS, the mean D_m and N_w values at 2.5 km above the ground surface were analyzed. Notably, there was a significant degree of spatial heterogeneity in each panel. The general conclusion is that continental PSs exhibit a higher D_m than do oceanic PSs. Usually, continental rainfall is associated with high convective activity in which

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clouds produce large raindrops. Over land, small raindrops are lifted by updrafts, whereas large raindrops are formed from the melting of larger ice crystals. In contrast, oceanic rainfall is accompanied by the formation of weak updrafts and the development of a low melting layer, which impedes the formation of large raindrops and results in a high concentration of small raindrops (Saha et al., 2022; Seela et al., 2018). Moreover, D_m decreases with increasing latitude, a trend that is especially notable in high-latitude marine regions (refer to Fig. S2c in the Supplementary Material). Cha et al. (Cha and Yum, 2021) noted that snow primarily comprises small particles (diameter < 1 mm). In high-latitude shallow PS, snowfall may become more frequent from the middle to high latitudes, which can result in a decrease in D_m. Notably, the height and thickness of the melting layer may influence raindrop growth (Hu et al., 2024). With increasing latitude, the melting layer becomes thinner, thus reducing the conditions necessary for raindrop growth, which may lead to the formation of a larger number of small raindrops. In the oceanic regions within subtropical shallow PS, the higher sea surface temperature in the tropics is more conducive to convection formation and development. Moreover, D_m varies among the eight clusters in a specific region. For example, in the Amazon region, moderate PS exhibits a lower D_m than deep PS does.

Similar to D_m, there is a distinct contrast in N_w between continents and oceans. Continental rainfall is usually associated with the cold rain mechanism, whereby raindrops grow as ice particles. In contrast, oceanic rainfall is associated with a warm rain regime, in which raindrops grow via a collision-agglomeration mechanism. Consequently, N_w over land is less than that over oceans (Suh et al., 2016). For the same PS, N_w is high in areas with small D_m values and conversely low in areas with large D_m values. For example, in extreme deep PS, the D_m value over the eastern near-equatorial Pacific Ocean, which reaches approximately 1.18 mm, is smaller than that of the other oceanic regions. However, N_w is significantly greater than those in the other regions. In strong PS, the D_m values in near-equatorial Africa and the eastern United States are greater than those in other regions, but the N_w values are lower than those in other regions. It is possible that D_m and N_w may be negatively correlated for the same PS.

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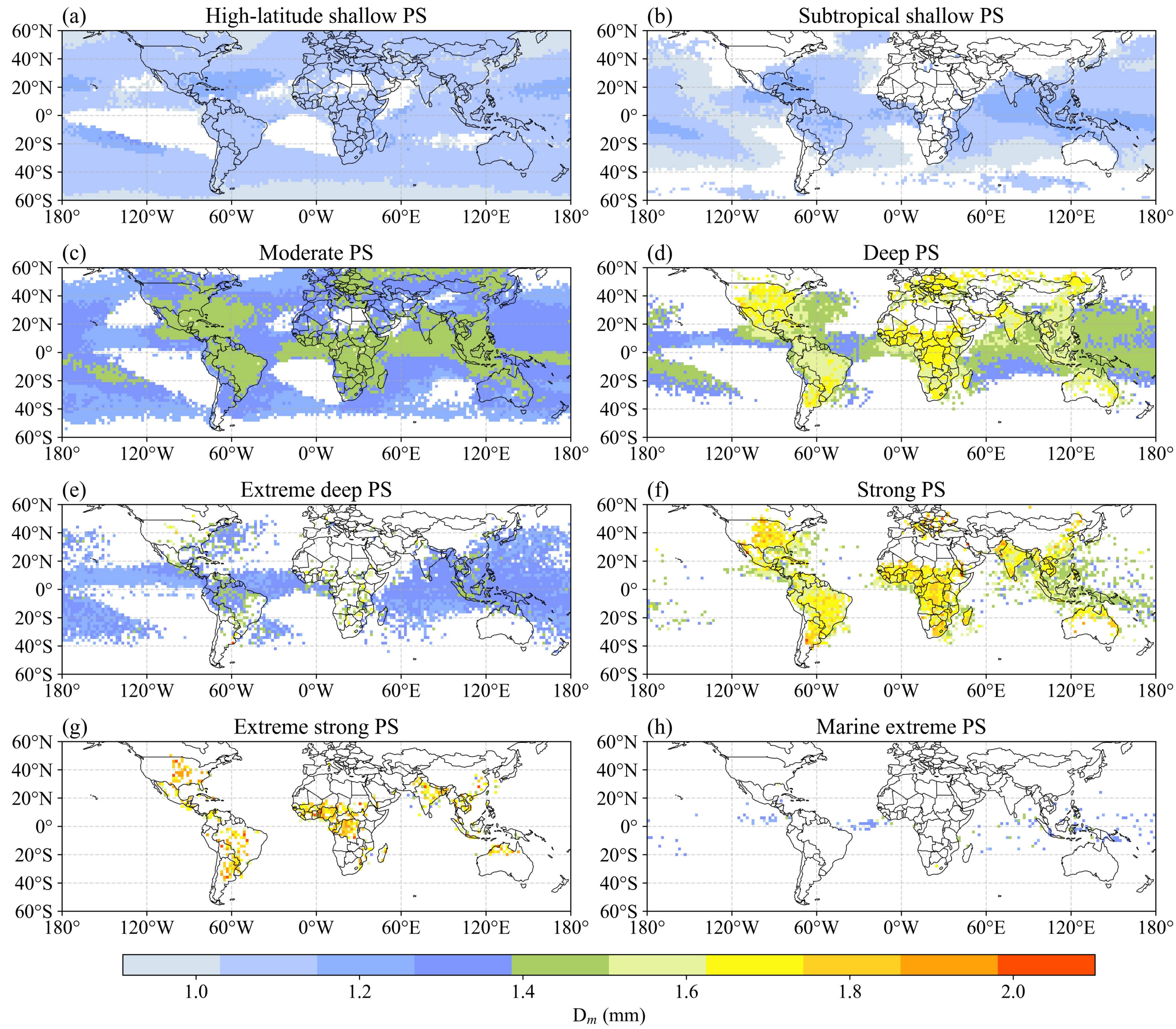

Figure 2. Spatial distributions of the mass-weighted mean diameter (D_m) for the eight PS clusters at a height of 2.5 km.

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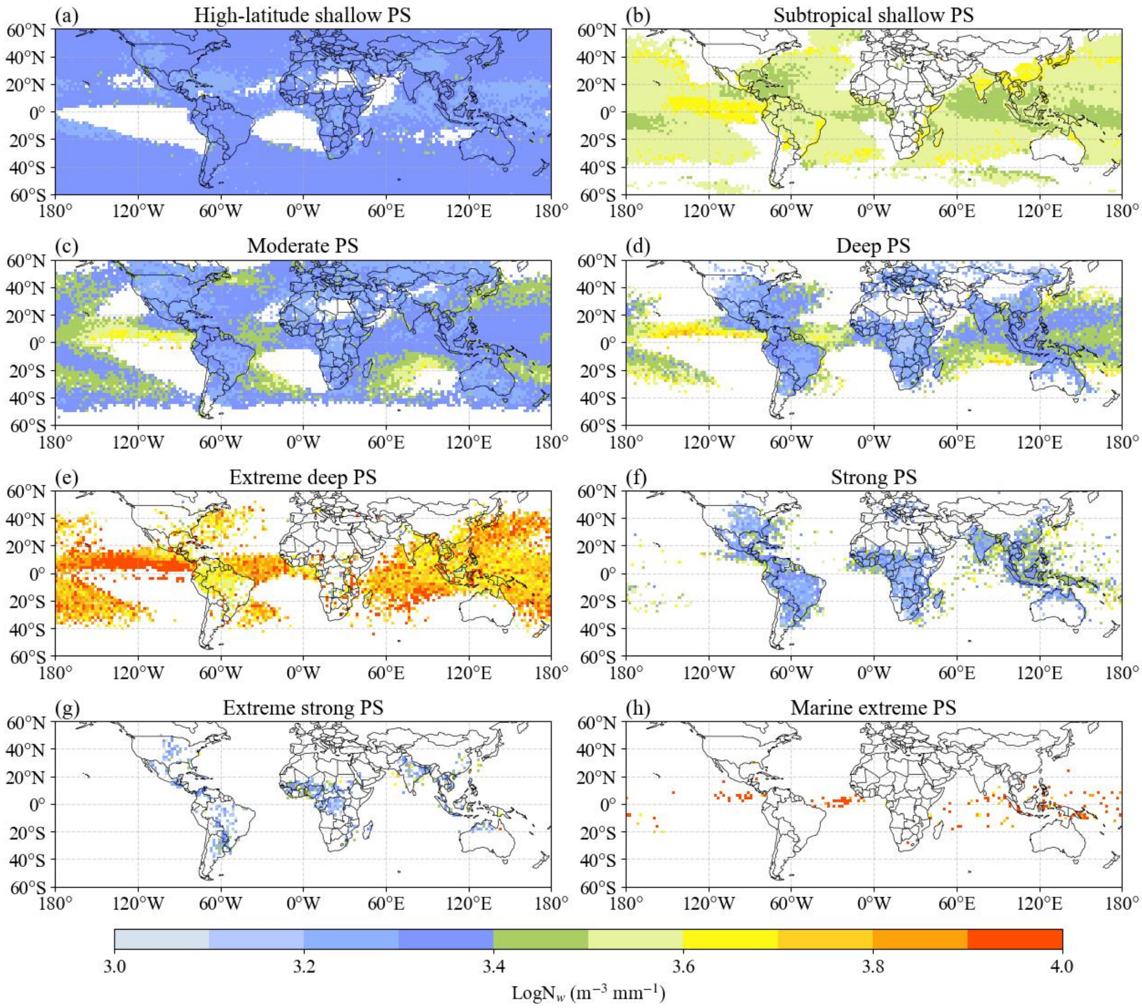

Figure 3. Similar to Fig. 2. but for log10(N_w).

3.3. Vertical structure of the different PS types

The contoured frequency by altitude diagrams (CFADs) of D_m, N_w, and the maximum radar reflectivity for the eight clusters are shown in Fig. 4/5/6. Figure 4 shows the CFAD of the maximum radar reflectivity profiles. The results revealed high echo tops for deep PS, extreme deep PS, strong PS, and extreme strong PS, and low echo tops for high-latitude shallow PS and subtropical shallow PS. Extreme strong PS attained an echo top height greater than 18 km, and it also exhibited the strongest convection at the middle level. Its geographic distribution was exclusively terrestrial, which is consistent with other studies concluding that deep convective cores occur mostly over land (Houze Jr. et al., 2015). Extreme deep PS and marine extreme PS exhibited sharper decreasing trends from 6–12 km than that in extreme strong PS. Therefore, extreme strong PS encompassed a greater amount of supercooled liquid droplets or large ice–water vapor condensates produced by strong

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convective updrafts than that in extreme deep PS and marine extreme PS (Jiang, 2012). Owing to the lack of strong updrafts in extreme deep PS and marine extreme PS, the reflectivity rapidly decreased with height above the freezing level. Table 1 indicates that the land proportion of extreme strong PS was much greater than that of extreme deep PS and marine extreme PS. Additionally, land indicates a dry adiabatic lapse rate, which results in greater buoyancy and allows for stronger updrafts to lift ice crystals higher into the atmosphere. As a result, the maximum radar reflectivity in the middle levels at high altitudes decreased more slowly in extreme strong PS. High-latitude shallow PS and subtropical shallow PS yielded low echo tops of less than 6 km, indicating low convective intensity. Therefore, subtropical shallow PS could be identified as being associated with isolated shallow convection over the ocean, especially the region dominated by the subtropical high.

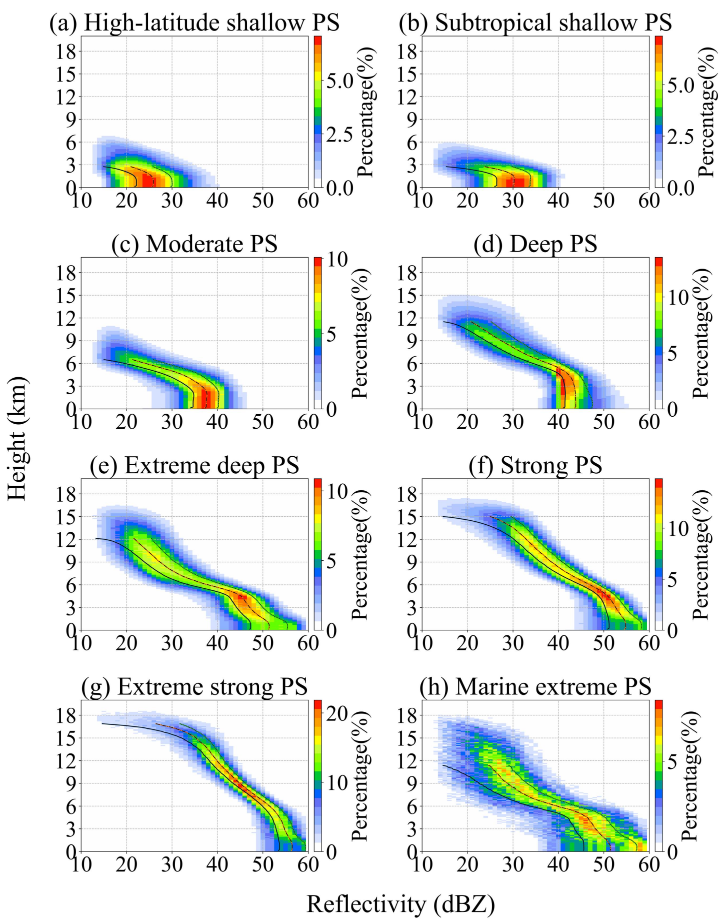

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Figure 4. Contoured frequency by altitude diagrams (CFADs) of the maximum radar reflectivity for the eight distinct PS clusters. The solid lines indicate the 25th percentiles; the dashed-dotted lines indicate the 50th percentiles; the dotted lines indicate the 75th percentiles.

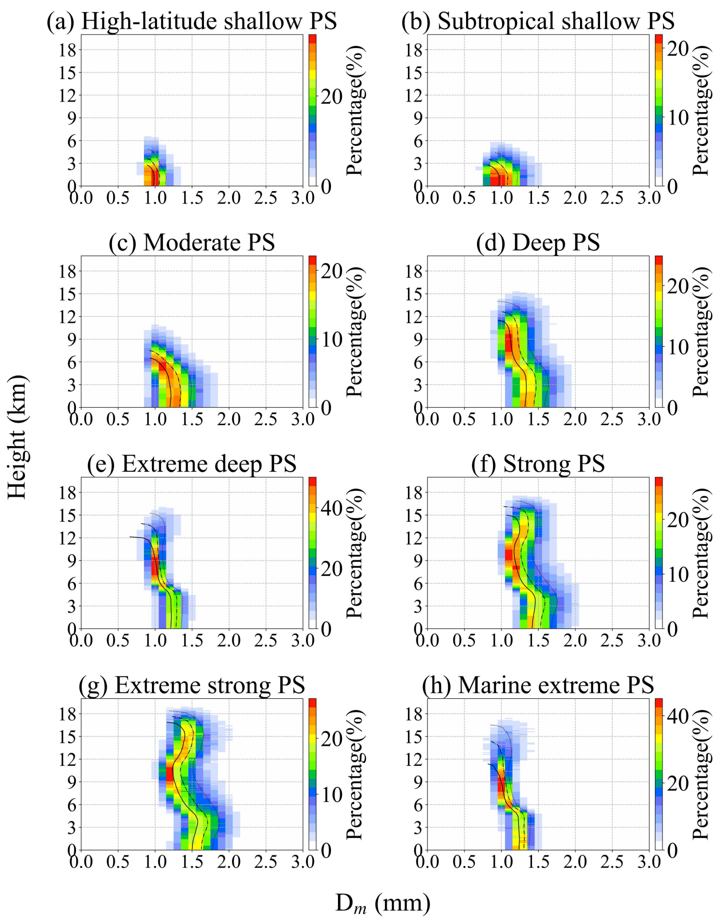

Figure. 5. Similar to Fig. 4, but for D_m.

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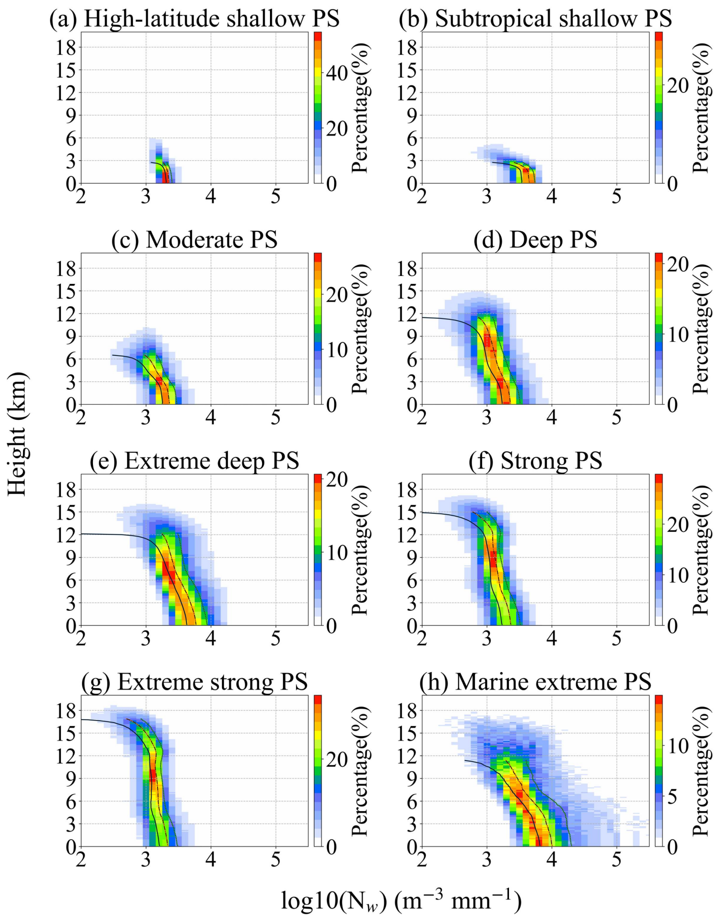

Figure. 6. Similar to Fig. 4, but for log10(N_w).

Figure 5 shows the CFAD of D_m for the eight types of PSs. Generally, deep convections (deep PS, extreme deep PS, strong PS, extreme strong PS, and marine extreme PS) produce different D_m values in the regions above and below approximately 5 km. Moreover, strong PS and extreme strong PS exhibited wider distributions than those of extreme deep PS and marine extreme PS. For deep PS, strong PS, and extreme strong PS, D_m below 4.8 km did not change much or slightly increased along with height, but the value decreased between 4.8 and 6.9 km. In extreme strong PS, the vertical structure of D_m was more complex. Extreme strong PS exhibited three regimes according to the variations in D_m. The first regime was observed between 0 and 4.1 km, where D_m increases with altitude. This is consistent with other papers involving the use of ground-based radar observations and reporting that D_m of deep convective precipitation decreases with decreasing height near the surface (Marzuki et al., 2023). The observed decrease in D_m may be related to the continued breakdown of large isolated raindrops in the atmosphere. The second regime was observed above the freezing level, from 4.1 to 10 km, where D_m decreases with altitude. In this regime, the updraft in deep convection was decreased (Uma and Rao, 2009). The decline in updraft decreased the size of the particles that can be retained in the cloud. Finally, the third regime was observed between 10 and 18 km, where D_m increases with altitude and where strengthened updrafts are often observed (Becker and Hohenegger, 2021). Although both high-latitude shallow PS and subtropical shallow PS were shallow PSs, subtropical shallow PS had a wider distribution of D_m than high-latitude shallow PS. One possible reason is that in shallow oceanic convection, the breaking of large raindrops broadens the DSD.

Figure 6 shows the CFAD of log10(N_w) for the different types of PSs. In general, N_w decreases with increasing altitude. The distribution range of N_w for shallow PSs was relatively small. Moreover, the N_w distribution range of subtropical shallow PS was larger than that of high-latitude shallow PS. Among PSs with intense convection, PSs with a greater proportion of land coverage exhibited more concentrated N_w values, whereas PSs with a greater proportion of ocean coverage exhibited higher N_w values. For example, the N_w values of strong PS and extreme strong PS were smaller and narrower than those of ocean-dominated deep PS, extreme deep PS and marine extreme PS. This finding is consistent with the conclusions of other studies (Kumar et al., 2024). One possible explanation is that the slower updrafts over ocean regions result in higher concentrations of smaller condensates at lower altitudes.

3.4. DSD characteristics at a height of 2.5 km

Figure 7a-h show the frequency distributions of the mean D_m and log10(N_w) values observed at 2.5 km above ground level. The mean D_m values for the eight types of PSs were 0.85, 0.89, 1.36, 1.50, 1.30, 1.61, 1.71, and 1.32 mm, and the corresponding log10(N_w) values were 3.23, 3.45, 3.36, 3.39, 3.83, 3.36, 3.35, and 4.45 $m^{-3}\,mm^{-1}$, respectively, as detailed in Table 1. Generally, all the distributions shown in Fig. 7a-h greatly deviate from the parameters of continental convection and maritime convection defined by Bringi et al. (2003). One reason is that the mean values of D_m and N_w for one PS were considered here, whereas Bringi et al. (2003) separated the observation samples into stratiform and convection samples. Moreover, the DSDs observed by disdrometers are generally cumulative observations of a single storm at one fixed location and differ from the results for each PS in this study, which represent the instantaneous occurrence of a storm. With the most intense convection at the middle level, extreme strong PS was the closest to continental convection (Fig. 7d), whereas marine extreme PS was the closest to maritime convection (Fig. 7e). For most PSs, D_m and N_w were negatively correlated, with greater dispersion of D_m than that of N_w. Moreover, the shallow PSs, such as high-latitude shallow PS, exhibited lower D_m and N_w values and more concentrated distributions than those of the deep PSs, such as those in deep PS.

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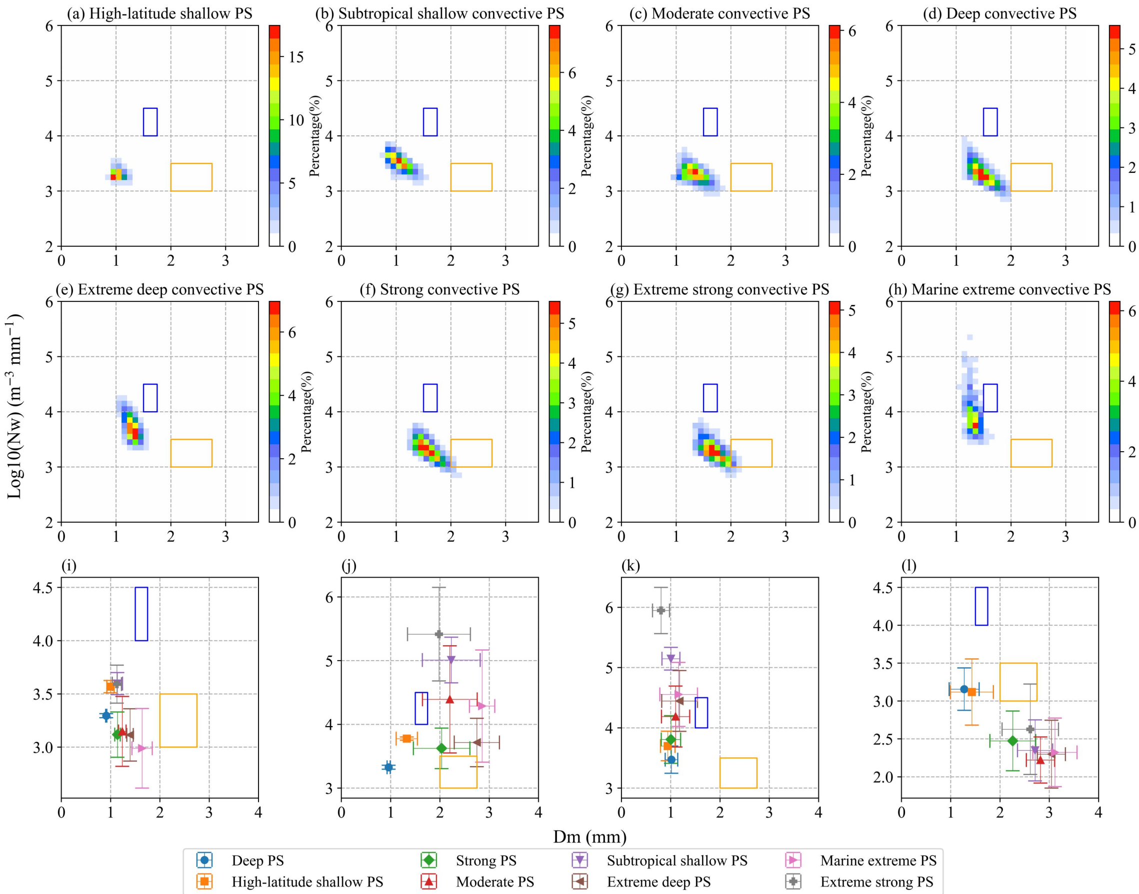

Figure 7. (a-h) Two-dimensional frequency distributions of D_m and log10(N_w) at a height of 2.5 km, and (i-l) statistical values of log10(N_w) and D_m for each PS (the bar indicates one standard deviation). (i) Mean values of D_m and log10(N_w), (j) MAX-D_m and MAX-log10(N_w), (k) MAX-log10(N_w) and D_m at its corresponding position, and (l) MAX-D_m and log10(N_w) at its corresponding position for each PS. (the blue and orange rectangles denote the maritime and continental convective clusters, respectively, in D_m and log10(N_w) space from Bringi et al. (2003)).

To further compare the mean D_m and N_w values of the different clusters, Figure 7i shows a summary of the mean D_m and N_w values, with the standard deviation for each type of PS. Marine extreme PS showed a significant abnormal value of N_w, whereas the N_w value of extreme deep PS slightly deviated from those of the other PS. However, if only three extremely deep PSs with the highest echo tops, as detailed in Table 1 (strong PS, extreme strong PS, and marine extreme PS), were considered, it could be concluded that the larger the D_m value is, the smaller the N_w value. Moreover, the other PSs exhibited very similar N_w values. These results might suggest that in deep convection, the DSD parameters at the near-surface level are related to convection intensity parameters. Ni et al. (2019) revealed that the dual-frequency ratio between the Ku and Ka

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bands at 12 km was positively correlated with intensity parameters such as MAXHT20/30, partly because stronger updrafts could hold larger ice particles in clouds. However, in swallow convection systems such as those in high-latitude shallow PS and subtropical shallow PS, the relationship did not hold, which rendered the relationship between microphysical parameters and convection parameters complex.

Note that although the mean D_m and N_w values represent the overall features of DSDs in one PS, they do not capture the variety of DSDs in each PS. For example, the DSD might differ between convective and stratiform regions, where the N_w–D_m relationships might vary. To comprehensively demonstrate the microphysical features of PSs, Figure 7j shows the mean MAX-D_m and MAX-N_w values of each PS at 2.5 km above ground level. For extreme PS (extreme deep PS, strong PS, extreme strong PS, and marine extreme PS), a negative correlation was found between MAX-D_m and MAX-N_w, similar to the mean D_m and N_w values shown in Fig. 7h. However, for the non-extreme PS, MAX-D_m and MAX-N_w exhibited positive correlations. A similar relationship is also shown in Fig. 7k, which suggests a relationship between MAX-N_w and the corresponding D_m value in the MAX-N_w pixels of each PS. Nevertheless, as shown in Fig. 7k, the D_m values of all eight types of PSs were very close. Nevertheless, it could be also found that in the non-extreme PS the D_m increases with MAX-N_w, while in the extreme PS, the D_m decreases with MAX-N_w. Figure 7l shows the relationship between MAX-D_m and the corresponding N_w value in the MAX-D_m pixels of each PS. Interestingly, for all eight types of PSs, MAX-D_m and N_w showed significantly negative correlations. Note that MAX-D_m and MAX-N_w in Fig. 7j are the maximum values for one PS and usually do not occur in the same pixel. Figure 7k-l show the N_w–D_m relationship observed at the same location. Overall, the conclusions generally indicated that deep PSs yield larger MAX-N_w or MAX-D_m values than shallow convection PSs do. Overall, extreme PS exhibited negative correlations between N_w and D_m, whereas non-extreme PS demonstrated positive correlations.

Ryu et al. (2021) analyzed DSDs during three types of heavy rainfall events with different rain intensities. They also reported that D_m increases with increasing rainfall intensity, whereas N_w decreases with increasing rainfall intensity. In this study, we saw a positive relationship between the increase in D_m and MAXHT20 in extreme PS. However, extreme strong PS attained the highest MAXHT20 value, but its precipitation rate was lower than that of extreme deep PS and marine extreme PS. These results suggest a complex relationship between the microphysical parameters and convection features, especially in deep and intense convection systems. Notably, in extreme convection, with strong convection at the top of the storm, attenuation becomes notable at low storm levels, which might influence the retrieval of microphysical parameters. To assess the impact of attenuation on the D_m-N_w relationship, ground-based observations of microphysical properties from disdrometers are needed. Finally, we considered the PS as a whole and did not account for the variations in the D_m and N_w values of each PS. The microphysical characteristics varied among different pixels. The mean or maximum values of D_m and N_w only reflect part of the total process. Therefore, analyses on the basis of pixel-level observations would improve this work.

To gain further insight into the primary microphysical processes associated with the various PS, we employed an investigative approach analogous to that utilized by Kumjian and Prat (2014). To prevent the influence of ground-based

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clutter, ΔZ_e and ΔD_m values were calculated as the difference between Z_e and D_m at 2 and 3 km above the ground. Specifically, $\Delta Z_e = Z_e^{2km} - Z_e^{3km}$ and $\Delta D_m = D_m^{2km} - D_m^{3km}$ are calculated. Fig. 8 shows the frequency pattern of ΔZ_e versus ΔD_m for the eight types of PSs. An increase (decrease) in Z_e and D_m indicates that coalescence (breakup) processes dominate. Balanced breakup and coalescence processes result in an increase in Z_e but a decrease in D_m. In contrast, a decrease in Z_e and an increase in D_m are due to predominate evaporation or size sorting processes (Wen et al., 2023).

The microphysical processes of the different types of PSs were significantly distinct. Notably, the microphysical processes were dominated by coalescence in the two types of shallow PS (Fig. 8a-b). Previous studies have demonstrated that high-latitude shallow PS are more likely to experience the condensation of rain droplets into snow due to the low temperatures in these regions. (Thompson et al., 2015). Meanwhile, the coalescence process plays an important role in tropical oceanic shallow convective precipitation (subtropical shallow PS) as demonstrated by Li et al. (2024). Balanced breakup and coalescence processes in the microphysical processes of extreme PS accounted for more than 40% of the total microphysical processes, significantly exceeding other three types of microphysical processes. The microphysical processes may reach an equilibrium state under high rainfall rates, in which the coalescence and breakup of raindrops are nearly balanced. Extreme deep PS and marine extreme PS encompassed a higher percentage of coalescence processes than strong PS and extreme strong PS did, whereas strong PS and extreme strong PS encompassed a higher percentage of breakup processes.

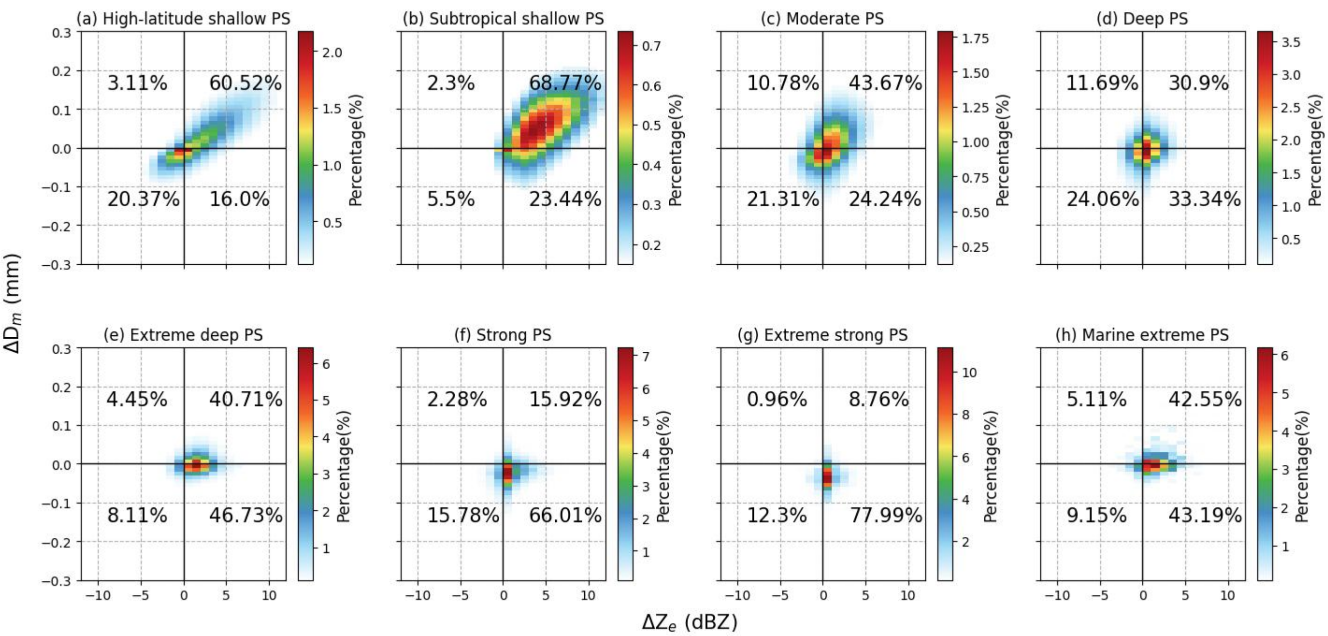

Figure 8. Frequency pattern of ΔZ_e versus ΔD_m between 2 and 3 km for the eight PS clusters.

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3.5. Seasonal and diurnal cycles

In this study, seasons were categorized by fixed calendar months. The Northern Hemisphere seasons were defined as spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). Conversely, the Southern Hemisphere seasons followed the opposite pattern: spring (September–November), summer (December–February), autumn (March–May), and winter (June–August). Based on this classification, the subsequent analysis examines seasonal and diurnal variations in PS frequency and microphysical parameters. Figure 9 shows the cycles of PS occurrence. Overall, the seasonal and diurnal cycles differed among the eight types of PSs. Moderate PS, deep PS, strong PS, and extreme strong PS exhibited cycles like those of continental convection systems, with peaks in the afternoon and in summer. Dominated by tropical shallow convection over the ocean (Fig. 1), subtropical shallow PS occurred mostly between 0 and 5 a.m. and was more frequent during the autumn season than during the other seasons, with the lowest occurrence during the spring season. The other types of PS (high-latitude shallow PS, extreme deep PS, and marine extreme PS) did not show obvious diurnal cycles, except that high-latitude shallow PS indicated a low peak at approximately 6 am in winter and a valley before noon in summer. High-latitude shallow PS occurred infrequently in winter. Extreme deep PS occurred more frequently in summer and autumn, with fewer occurrences in winter. Note that marine extreme PS did not demonstrate obvious seasonal discrepancies, but shown a peak at night in the summer. Specifically, strong PS and extreme strong PS with a higher proportion over land exhibit a peak occurrence around 3 p.m. in the afternoon, while extreme deep PS and marine extreme PS with a higher proportion over the ocean shows no distinct peak, with its frequency distributed relatively evenly throughout the day. This difference reflects the land-ocean contrast in extreme PS, which is consistent with findings from other related studies (Wang and Tang, 2020).

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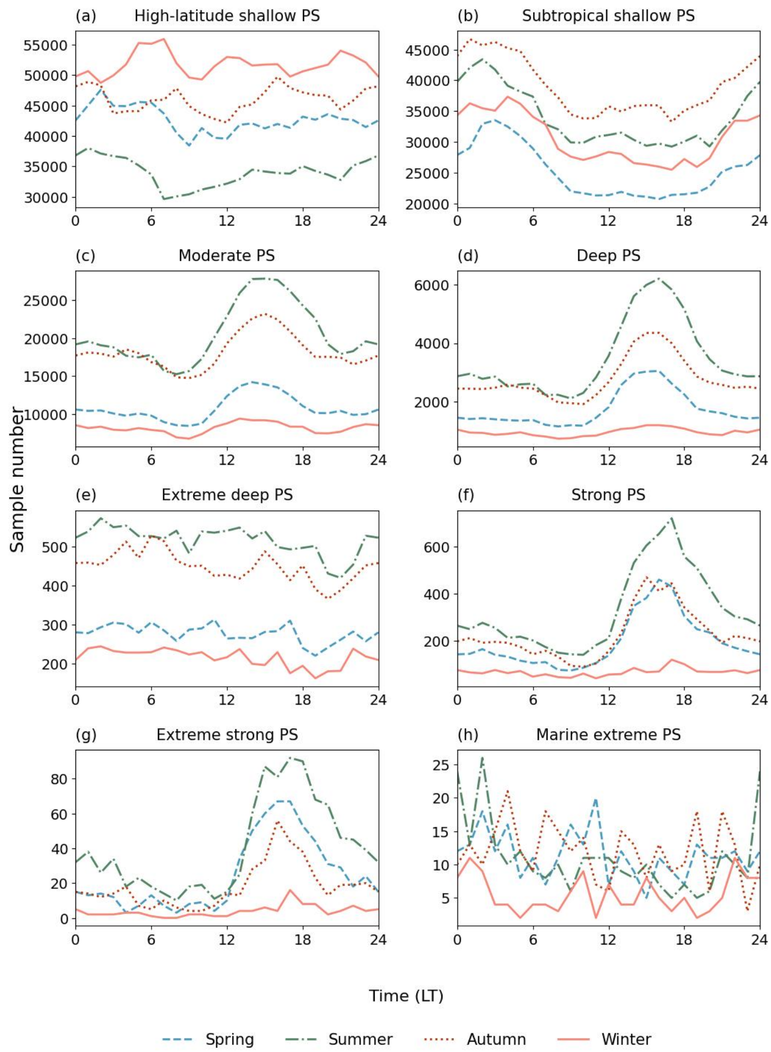

Figure 9. Diurnal variations in the sample sizes of the eight distinct PS clusters across the four seasons.

Figures 10 and 11 show the seasonal and diurnal cycles of D_m and N_w, respectively. The diurnal cycles of D_m were similar with those of PS occurrence to some extent. For example, in moderate PS, deep PS and strong PS, both the occurrence and D_m have peaks in the around 15 pm. One connection between these two parameters is that environments that favor storm occurrence could also facilitate the development of stronger updrafts, which could promote the formation of large particles in clouds. Nevertheless, discrepancies are obvious between the cycles of occurrence and D_m. For example, the D_m in the extreme strong PS did not show obvious diurnal variations. The high-latitude shallow PS shows a peak in the summer (Fig. 10a), which is not found in the diurnal cycle of occurrence (Fig. 9a). In subtropical shallow PS, the diurnal cycle of D_m (Fig. 10b) was the opposite to that of PS occurrence (Fig. 9b). The diurnal cycles of N_w were basically different with those of D_m and occurrence. In subtropical shallow PS, moderate PS, deep PS, and strong PS, the N_w peaked in the morning.

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Nevertheless, the diurnal cycles of subtropical shallow PS, moderate PS, and deep PS also differed. For example, N_w of subtropical shallow PS at night was low, whereas N_w of shallow convective PS and moderate PS at night was very close to its peak. Extreme deep PS and marine extreme PS did not exhibit obvious diurnal cycles of N_w. The extreme strong PS shown low values of N_w in the afternoon and little variations at night. For high-latitude shallow PS, diurnal variation is not clear except in the summer when the N_w in the afternoon is the lowest.

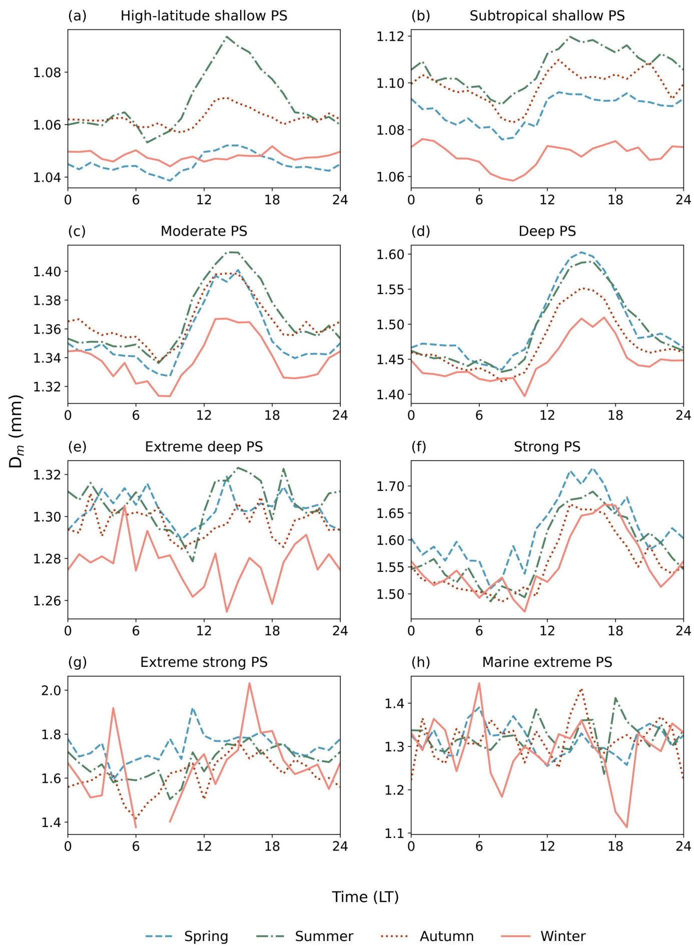

Figure 10. Similar to Fig. 9 but for mean D_m value.

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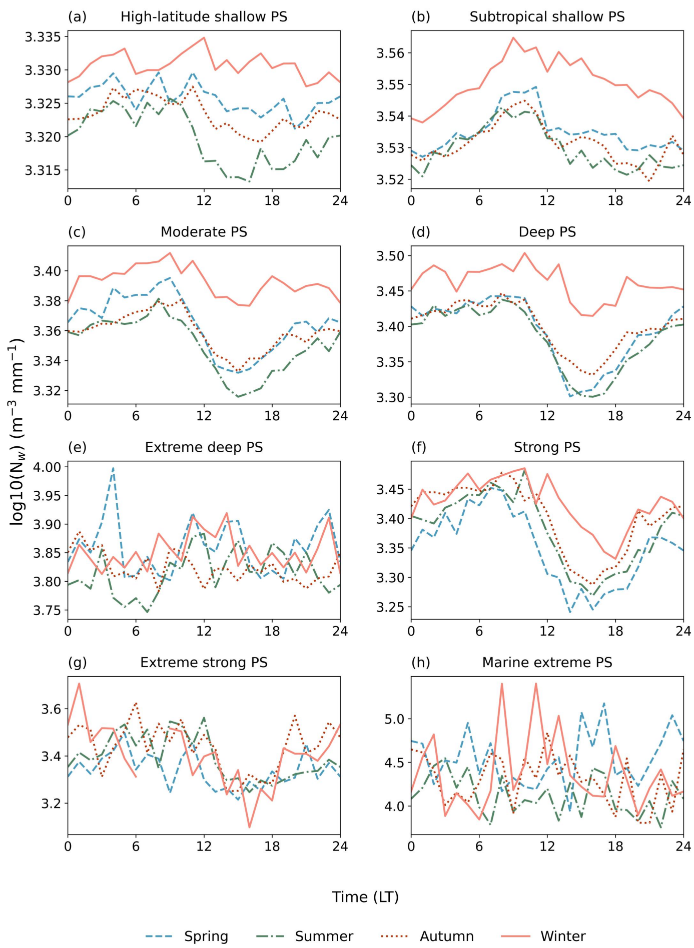

Figure 11. Similar to Fig. 9 but for the mean log10(N_w) value.

Similar to the diurnal cycles, the annual cycles of D_m and N_w were opposite in subtropical shallow PS, moderate PS, and deep PS, of which D_m was the lowest and N_w was the largest in winter. Nevertheless, there were also differences in the annual cycles of the three types of PSs. For example, in subtropical shallow PS, D_m was the largest in summer, followed by autumn and spring, whereas the N_w values during the three seasons were very close. Among the extreme PS, N_w and D_m did not exhibit obvious annual cycles. For high-latitude shallow PS, the highest D_m value occurs in summer and the D_m in winter and spring were comparable. However, the annual cycle of N_w attained the largest value in winter and the lowest value in summer.

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4. Conclusions

In this study, GPM DPR data were used to objectively classify global PS and analyze the microphysical characteristics of the different types of PS. The main conclusions are as follows:

1). By conducting an objective classification of global PSs via key parameters such as the convective intensity, radar reflectivity, and DSD parameters, eight distinct types of PSs were identified. These systems were classified on the basis of their unique microphysical and convection properties, providing a detailed understanding of the different precipitation processes worldwide. The eight types of PSs identified are as four types of regular/non-extreme PS (high-latitude shallow PS, subtropical shallow PS, moderate PS, deep PS) and four types of extreme PS (extreme deep PS, strong PS, extreme strong PS, marine extreme PS).

2). MAXHT20 is generally correlated with the precipitation rate, but this relationship is not clear for extreme PS. The relationship between MAXHT20 and D_m does not follow a simple linear pattern. For extreme PS, MAXHT20 is positively related to D_m at 2.5 km above the ground surface. This may reflect the relationship between higher cloud tops and greater liquid water contents in strongly convective PSs. However, for non-extreme PS, the relationship between MAXHT20 and D_m is more complex and may be influenced by variations in the physical processes of the different PS.

3). For the same type of PS, D_m over land is greater than that over the ocean. Additionally, D_m exhibits latitudinal variability, particularly in high-latitude shallow PS, where D_m decreases with increasing latitude. Additionally, continental rainfall is associated with lower N_w values due to the cold rain mechanism, whereas oceanic rainfall is associated with higher N_w values resulting from a warm rain regime. Shallow PS generally exhibit narrow distributions of both D_m and N_w, particularly in high-latitude shallow PS. Among the strong PS, PS with a higher land proportion exhibit more concentrated N_w values, whereas those with a greater ocean proportion exhibit larger N_w values. However, the distribution of D_m is the opposite: PS with a higher ocean proportion exhibit more concentrated D_m values than land-dominated PSs do.

4). The different PS exhibit distinct microphysical processes. In shallow convective PS, such as subtropical shallow PS and high-latitude shallow PS, coalescence processes largely shape the microphysical characteristics, indicating the aggregation of small raindrops in these PS. In contrast, extreme PSs are characterized by balanced breakup and coalescence processes, highlighting a more complex interaction between raindrop formation and breakup. These results emphasize the varying mechanisms that govern microphysical behavior across the different types of PSs. PS types with high precipitation rates are dominated primarily by balanced breakup and coalescence processes, whereas shallow PSs are characterized mainly by coalescence.

5). The seasonal and diurnal cycles of PSs and their microphysical parameters vary significantly, with distinct patterns observed in different clusters: clusters dominated by continental convection indicate peaks in the afternoon and summer, whereas tropical and high-latitude systems exhibit unique seasonal and diurnal cycles, often with opposite trends between D_m and N_w.

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Classifying PS is essential for increasing the understanding of the microphysical processes that govern cloud development and precipitation formation across various climatic regimes. This classification enables the identification of specific mechanisms that influence rainfall characteristics, such as droplet formation, growth, and distribution, which are vital for accurate weather predictions and climate modeling. This study revealed the global distribution characteristics of different types of PS and elucidated the variations in microphysical properties across regions with distinct climatic and geographic conditions.

In this study, each PS was treated as integrated entity, without considering the variations in D_m and N_w within each system. Microphysical properties can vary significantly at the pixel level, and relying solely on average or maximum D_m and N_w values captures only part of the overall process. Future work should focus on analyzing pixel-level observations to better understand the characteristics of microphysical parameters within PS. Furthermore, investigating the relationships between microphysical parameters and convective parameters will be a key focus of future research. By analyzing the interactions between these parameters, it is possible to reveal the influences of microphysical characteristics on convective intensity and precipitation patterns, providing a more detailed perspective for accurately predicting and understanding precipitation phenomena.

Data Availability. The GPM-DPR (version 07A) data from the NASA/G-oddard Space Flight Center are available at https://disc.gsfc.nasa.gov/datasets/GPM_2A-DPR_07/summary. All statistics and visualization are operated with Anaconda Individual Edition Python version 3.8.3 (Free Download | Anaconda, accessed on 10 April 2022).

Author contributions. XZ and XN conceptualised and planned the research study. XZ conducted the satellite data analysis with support from XN and drafted the initial manuscript. XN and JZ reviewed and revised the manuscript to refine its content.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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