Characteristics of Raindrop Size Distributions
during Meiyu Season in Mount Lushan, Eastern China

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Abstract

Meiyu front precipitation makes the region prone to frequent floods, mudslides, landslides, and other disasters and has been the focus of ongoing and challenging meteorological research. Investigation of the Raindrop size distribution (RSD) is essential for exploring the characteristics and underlying physical precipitation processes. In this study, the precipitation characteristics in Lushan mountainous areas during the Meiyu season were investigated using laser disdrometer observed RSD data from 2016 to 2020. For the average spectra of five rain rate classes, the concentrations of large raindrops (> 0.5 mm) increased with rain rate (R), whereas the concentrations of small raindrops (≤ 0.5 mm) increased only under rain rates higher than 10 mm h⁻¹. The gamma distribution parameters of N₀ (intercept parameter) and Λ (slope parameter) increased/decreased with rain rate, and the shape
1. Introduction

More accurate precipitation prediction and related physical mechanisms researches are vital for meteorology, climatology, and hydrology. Investigation of the raindrop size distribution (RSD) is essential for exploring the characteristics and underlying physical precipitation processes (Rosenfeld and Ulbrich 2003). The characteristics of RSD from ground-based observations are synthetic and address the microphysics and thermal dynamics within, or outside, precipitation clouds (Rosenfeld and Ulbrich 2003; Thomas et al. 2021). The parameterization of RSD is fundamental to improve the microphysics of clouds and precipitation in numerical model simulations (Haddad et al. 1996; Milbrandt and Yau 2005; Rotstayn 1997; Sun 2005; Tapiador et al. 2014, 2019). RSD researches have contributed to improving quantitative precipitation estimations (QPEs) for weather radar and satellite observations (Atlas et al. 1999; Chandrasekar and Bringi 1987; Chandrasekar et al. 2003; Rosenfeld and Ulbrich 2003; Seto et al. 2021; Tokay and Short 1996; Ulbrich and Atlas 1998; Zhang et al. 2001; Zhao et al. 2011).

The characteristics of RSD vary according to geographical locations (Chang et al. 2009; Chen, B. et al. 2017; Dolan et al. 2018; Luo et al. 2020; Niu et al. 2010; Radhakrishna et al. 2020; Sauvageot and Lacaux 1995; Zhao et al. 2011), climate regimes (Bringi et al. 2003; Yamaji et al. 2020), seasons (Chakravarty and Raj 2013; Seela et al. 2018; Wen et al. 2017), and rain types (Atlas and Ulbrich 2006; Chen et al. 2013, 2016; Thompson et al. 2015; Tokay and Short 1996). RSD characteristics and their variations may differ considerably between different disdrometer instruments (Angulo-Martinez et al. 2018) or even between the same instrument but within a short distance (Tapiador et al. 2010). Systematic RSD studies have been performed over the past two decades to better understand the characteristics of RSD in the East Asian monsoon region. Statistical studies of RSD, ranging from northern China to the Tibetan Plateau have been conducted, and the RSD characteristics significantly vary in different regions. Physical processes between stratiform and convective rains also exhibit obvious differences in different climate regimes (Chen, B. et al. 2013, 2017; Ji et al. 2019; Luo et al. 2020; Niu et al. 2010; Wen et al. 2016; Zhang et al. 2019).

Meiyu is a climatological phenomenon that affects the weather and climate in eastern Asia and usually induces abundant precipitation (Ding 1994). The Meiyu/Baiu front is characterized as a quasi-stationary front along the north edge of a subtropical high stretching from the Yangtze River basin to south Japan and presents unique weather systems during the Meiyu season. Previous research has shown that heavy precipitation events and related flood disasters are likely caused by the Meiyu/Baiu front (Tao and Ding 1981; Xu et al. 2008; Yasunari and Miwa 2006; Zhao et al. 2019). Additionally, it can influence extreme precipitation in Mount Lushan by adjusting the low-level jet (Li et al. 2012). Hashimoto and Harimaya (2003) analyzed the Baiu RSD data obtained in south Japan using principal component analysis and found two principal components of variation of RSD, which could be attributed to the difference between convective and stratiform
precipitation. Different characteristics of RSD variation were obtained in their subsequent study, the major precipitation mechanism in the mature and dissipation stages of the Meiyu/Baiu convective clouds (Hashimoto and Harimaya 2005). Oue et al. (2010) and Oue et al. (2011) found and characterized different RSD with low echo-top and large \( D_m \) (radar reflectivity) in stratiform and convective rain zones within the Meiyu/Baiu frontal rainband in the Okinawa region by simultaneously applying a C-band polarimetric radar and a disdrometer. Chen et al. (2013) found that the mass-weighted diameter (\( D_m \)) and generalized intercept parameter \( N_w \) in eastern China were lower than those reported in Japan (Bringi et al. 2003). Wen et al. (2016) studied the RSD characteristics and differences in convective, stratiform, and shallow rains, higher \( N_w \) and lower \( D_m \) values than those of Chen et al. (2013) were obtained. More recently, Fu et al. (2020) studied RSD characteristics in central China and demonstrated different \( N_w \) and \( D_m \) values and different \( \mu-A \) and \( Z-R \) relationships. Although such studies have furthered the understanding of RSD in precipitation processes, few have focused on mountainous regions, and even less attention has been given to the impacts of mountainous topography on RSD characteristics and the related physical processes.

To understand the physical processes within the Meiyu precipitation concerning the high variety of RSD characteristics among different geographical locations, more RSD observations and studies are needed. The Lushan Mountains, with most peaks being more than 1000 m, are known as typical horst block mountains. They are in the northern Jiangxi Province, which faces Poyang Lake to the east and borders the Yangtze River in the north (Fig. 1a). The high mountainous topography of Mount Lushan can act as an elevated platform to investigate the interactions between aerosols, clouds, and precipitation because it is close to the cloud base or within the cloud directly (Duan et al. 2021; Guo et al. 2019). Continuous field observations of cloud and fog processes in Mount Lushan have been conducted since 2015 at the Lushan Cloud and Fog Experiment Station in Mount Lushan (29.57°N, 115.97°E, 1080 m ASL) (Fig. 1). The LPM is a ground-based optical disdrometer with a sampling area of 45.6 cm² and a temporal resolution of 1 min. The RSD data were collected every 1 min in a \( 22 \times 20 \) matrix that recorded the raindrop numbers of each diameter and velocity bin. The diameter ranged from 0.125 mm to larger than 8 mm, and the velocity ranged from 0 to 20 m s\(^{-1}\).

2. Data and methods

2.1 Observations

A Laser Precipitation Monitor (LPM) from Thies CLIMA was set at the observational platform of the Lushan Cloud and Fog Experiment Station in Mount Lushan (29.57°N, 115.97°E, 1080 m ASL) (Fig. 1). The LPM is a ground-based optical disdrometer with a temporal resolution of 1 min. The RSD data were collected every 1 min in a \( 22 \times 20 \) matrix that recorded the raindrop numbers of each diameter and velocity bin. The diameter ranged from 0.125 mm to larger than 8 mm, and the velocity ranged from 0 to 20 m s\(^{-1}\).

2.2 Methods

a. LPM data quality control

The effective sampling area for laser optical sensors is affected by the border effects (Battaglia et al. 2010). In the \( i \)th size class, the effective sampling area is \( 228 \times (20 - D_i) \) mm\(^2\) and \( D_i \) (mm), which is the mean diameter for the \( i \)th size diameter class (Jaffrain and Berne 2011). The incorrect records of small particles with high falling speed are named as the “margin fallers” and detected when they partially cross the sampling area (Yuter et al. 2006). Strong winds and splashing usually cause spurious particle recording, and according to previous studies, the empirical terminal velocity–diameter (V–D) relationship is constantly used to assess and eliminate spurious records (Chen, B. et al. 2013, 2017; Ji et al. 2019). In this study, we chose the empirical V–D relationship with the air density correction factor to assess the raindrop data (Atlas et al. 1973):

\[
V(D) = (9.65 - 10.3e^{-0.6D})\left(\frac{\rho_0}{\rho_a}\right)^{0.4},
\]

where \( \rho_0 \) and \( \rho_a \) (1.20 kg m\(^{-3}\)) are the air density at the observation level and sea level, respectively. The temperature and pressure data of the automatic meteorological station (AWS) of the Lushan Meteorological Bureau (29.57°N, 115.97°E, 1165 m) were used to retrieve the correction factor. Using the AWS data in June and the first half of July from 2016 to 2020, the average pressure and temperature during the Meiyu season were first calculated, and \( \rho_0/\rho_a \) was then de-
derived through the ideal gas state equation \((P = \rho RT)\). Finally, a correction factor of 1.0655 was obtained. Thus, the terminal velocity \(V(D_i)\) of each diameter bin \(D_i\) was achieved, and the particles out of the velocity range \(V(D_i) \pm 0.6V(D_i)\) were removed (Friedrich et al. 2013; Jaffrain and Berne 2011) (Fig. 2).

b. Raindrop size distribution parameters

The raindrop size distribution is depicted as the number concentration of raindrops \(N(D_i)\) (m\(^{-3}\) mm\(^{-1}\)) per unit volume from \(D_i\) to \(D_i + \Delta D_i\) in size class \(i\) and can be calculated using Eq. (2):

\[
N(D_i) = \sum_{j=1}^{20} \frac{n_{ij}}{A_i \cdot \Delta t \cdot V_j \cdot \Delta D_i},
\]  

(2)

where \(n_{ij}\) is the number of raindrops for the \(i\)th diameter bin and \(j\)th velocity bin, \(A_i\) (m\(^2\)) is the effective sampling area, \(\Delta t\) is the sampling time interval (60 s for LPM), \(V_j\) (m s\(^{-1}\)) is the average velocity of the \(j\)th velocity bin, and \(\Delta D_i\) (mm) is the width of each diameter bin.

The bulk microphysical parameters total number concentration \(N_T\) (m\(^{-3}\)), rainwater content \(W\) (g m\(^{-3}\)), rain rate \(R\) (mm h\(^{-1}\)), and radar reflectivity factor \(Z\) (mm\(^6\) m\(^{-3}\)) were calculated as follows:

\[
N_T = \sum_{i=1}^{22} \sum_{j=1}^{20} \frac{n_{ij}}{A_i \cdot \Delta t \cdot V_j},
\]  

(3)

\[
W = \frac{\pi}{6} \times 10^{-3} \cdot \rho_w \cdot \sum_{i=1}^{22} \sum_{j=1}^{20} D_i^3 \cdot \frac{n_{ij}}{A_i \cdot \Delta t \cdot V_j},
\]  

(4)

\[
R = 6\pi \times 10^{-4} \cdot \sum_{i=1}^{22} \sum_{j=1}^{20} D_i^3 \cdot \frac{n_{ij}}{A_i \cdot \Delta t},
\]  

(5)
where \( \rho_w \) is the density of water (1 g cm\(^{-3}\)). The mass-weighted mean diameter \( D_m \) (mm) and generalized intercept parameter \( N_w \) (m\(^{-3}\) mm\(^{-1}\)) were introduced to describe the bulk characteristics of RSD, which could be calculated according to Eqs. (7) and (8).

\[
D_m = \frac{\sum_{i=1}^{22} \sum_{j=1}^{20} N(D_i) \cdot D_i^4 \cdot \Delta D_i}{\sum_{i=1}^{22} N(D_i) \cdot D_i^3 \cdot \Delta D_i},
\]

\[
N_w = \frac{4^4}{\pi \rho_w} \left( \frac{10^{1.5} \cdot W}{D_m^4} \right).
\]

The gamma distribution proposed by Ulbrich (1983) was used to describe the distribution of the raindrop size, as shown in Eq. (9).

\[
N(D) = N_0 D^\mu e^{-AD},
\]

where \( D \) (mm) is the diameter, \( N_0 \) (m\(^{-3}\) mm\(^{-1-\mu}\)) is the intercept parameter, \( \mu \) is the shape parameter, and \( A \) (mm\(^{-1}\)) is the slope parameter.

In this study, a rain event was defined as when there were continuous spectra with no less than 30 min, and two events with a less than 1 h rain-free period would be regarded as 1 (Chen, B. et al. 2017; Tokay and Bashor 2010). The spectra with a rain rate of less than 0.1 mm h\(^{-1}\) or a total number of less than 10 would be treated as noise (Chen et al. 2013). During the Meiyu period from 2016 to 2020, a dataset of 186 rain events was derived from the quality-controlled observational data.

3. Results

3.1 RSD properties of different rain rates

The RSD of different rain rates has different characteristics (Chen, B. et al. 2013, 2017; Ji et al. 2019; Porcù et al. 2014). However, because of different geographic locations (e.g., Chen, B. et al. 2017; Ji et al. 2019) and rain types (e.g., Porcù et al. 2014; Chen et al. 2013), the RSD properties of different rain rates might vary. In this study, the rain rates were divided into five classes: 1) \( 0.1 \leq R < 1 \) mm h\(^{-1}\), 2) \( 1 \leq R < 5 \) mm h\(^{-1}\), 3) \( 5 \leq R < 10 \) mm h\(^{-1}\), 4) \( 10 \leq R < 100 \) mm h\(^{-1}\), and 5) \( R \geq 100 \) mm h\(^{-1}\). Samples with \( R \geq 5 \) mm h\(^{-1}\) contributed 79 % to the total sample numbers and 22.74 % to the precipitation amount, and the samples with \( 5 \leq R < 10 \) mm h\(^{-1}\) and \( R \geq 100 \) mm h\(^{-1}\) contributed 14.72 % and 62.54 %, respectively (Fig. 3). The percentages of sample counts and precipitation amounts were similar to the results for Nanjing, a city with a lower altitude in east China (Chen et al. 2013); however, there were more samples (0.32 %, 135 samples) with higher rain rates in Mount Lushan.

For large raindrops (> 0.5 mm), the number concentration increases with the rain rate and spectra rise in parallel. For small raindrops (< 0.5 mm), when the rain rates are lower than 10 mm h\(^{-1}\), the concentrations...
for smaller/larger than 0.0375 mm raindrops will decrease/increase, which concords with the “rotational movement” reported by Hashimoto and Harimaya (2003). When the rain rates exceeded 10 mm h$^{-1}$, the spectra tended to expand in parallel, and the concentrations of all diameter bins will rise with the rain rate. The average spectrum is like that of $5 < R < 10$ mm h$^{-1}$, but with a higher concentration at the smaller and larger ends of the diameter range, and a lower concentration at the middle diameter range (Fig. 4).

To compare the spectral characteristics for different rain rate classes, the standard deviation of the mass spectrum $\sigma_M = D_w / (4 + \mu)^{1/2}$ and normalized standard deviation of the mass spectrum $\sigma_M / D_w$, which were defined by Ulbrich and Atlas (1998), were used. To obtain the $\mu$ parameter from the RSD, the fitting methods were first compared. The maximum likelihood (ML) (Brawn and Upton 2007, 2008) and truncated moment (MM) (Ulbrich and Atlas 1998; Zhang et al. 2003) methods were used to estimate the parameters of the gamma distribution. The MM method fits better than the ML method in terms of RSD shape. For rain rates of $< 10$ mm h$^{-1}$, the ML method underestimates/overestimates the concentrations for large/small particles, and the ML method also slightly overestimates the larger diameter classes (diameter $> 0.5$ mm) for rain rates $\geq 10$ mm h$^{-1}$. For the entire dataset average spectrum, the ML method overestimates the concentrations in the diameter range of 0.5–3 mm and smallest diameter class (0.125–0.25 mm) and underestimates the concentrations in the 0.25–0.5 and $> 3.5$ mm ranges (Fig. 5).

Table 1 presents the correlation coefficient, absolute bias, relative bias, $N_r$, and $W$ for the observation and fitting results for the two fitting methods. The absolute bias and relative bias were calculated following Tokay and Bashor (2010). The ML method shows significant advantages over the MM method according to the correlation coefficients and absolute biases and is similar to observed results in the Tibetan Plateau (Chen, J. et al. 2017). However, the MM method shows superior results in terms of relative biases. For $N_r$, ML obtains better results for smaller rain rate classes ($< 10$ mm h$^{-1}$), and MM obtains better results for larger rain rate classes ($\geq 10$ mm h$^{-1}$). For the entire dataset, the two methods exhibit similar results. For $W$, the MM method shows superior results to the ML method. The results will be based on the MM method to further discuss the characteristics of Meiyu precipitation because it has advantages in terms of describing the RSD shape and estimating the precipitation.

Table 2 presents parameters and fitting results of the average spectra for different rain rates. According to Table 1, the $N_r$ and $W$ both increase with rain rate, and in Table 2, the $Z$, $D_w$, and $\sigma_M$ exhibit similar variations, meaning that the rising parameters have close relationships with diameter, spectra width, and rain rate. By contrast, $\log_{10} N_r$ and $\sigma_M / D_w$, which address concentration, diameter, and spectra shape, scarcely vary with rain rate. For the fitting results, $N_r$ and $A$ increase/decrease with rain rate, and $\mu$ varies little with rain rate and are negative for all rain rate classes. This differs from other observations (Chen, B. et al. 2013, 2016, 2017). The concentrations for small raindrops are slightly high and consequently lead to a left lower bending trend shape of the spectra, and negative $\mu$ values are derived (Figs. 4, 5).

3.2 Differences between stratiform and convective rains in Meiyu

a. Classification of stratiform and convective rains

It has been widely demonstrated that stratiform rains have quite different physical processes compared with convective rains (Bringi et al. 2003; Chang et al. 2009; Chen, B. et al. 2013, 2017; Ji et al. 2019; Zhang et al. 2019), as well as microphysical schemes and retrieval methods in remote sensing (Atlas and Ulbrich 2006; Chen, B. et al. 2017; Dolan et al. 2018; Rosenfeld and Ulbrich 2003; Ulbrich and Atlas 1998). To determine the differences between stratiform and
Fig. 5. Fitting results of the ML method (dash lines) and the MM method (dotted lines) for average spectra of each rain rate class (a)–(e) and the entire dataset. Blue lines indicate the observed spectra.

Table 1. Correlation coefficients, average absolute biases, average relative biases, $N_f$ (m$^{-3}$), and $W$ (g m$^{-3}$) of the fitting results using the ML and MM methods for each rain rate class and the entire dataset.

| R class | Corr. Coef. | Abs. Bias | Rel. Bias (%) | $N_f$ (m$^{-3}$) | $W$ (g m$^{-3}$) |
|---------|-------------|-----------|---------------|-----------------|-----------------|
|         | ML | MM | ML | MM | ML | MM | ML | MM | ML | MM | Obs. | ML | MM | Obs. |
| 0.1 ≤ $R < 1$ | 0.86 | 0.50 | 418 | 684 | 126.5 | 31.6 | 1526 | 1503 | 1216 | 0.09 | 0.05 | 0.05 |
| 1 ≤ $R < 5$ | 0.93 | 0.56 | 195 | 558 | 109.4 | 25.1 | 1614 | 2265 | 1475 | 0.26 | 0.17 | 0.17 |
| 5 ≤ $R < 10$ | 0.89 | 0.69 | 212 | 357 | 77.9 | 29.7 | 1983 | 2457 | 1818 | 0.56 | 0.41 | 0.42 |
| 10 ≤ $R < 100$ | 0.65 | 0.58 | 1433 | 1494 | 56.5 | 33.9 | 7288 | 5668 | 5469 | 2.29 | 1.34 | 1.32 |
| $R ≥ 100$ | 0.53 | 0.49 | 6721 | 6234 | 75.6 | 49.6 | 31846 | 17165 | 20152 | 15.19 | 6.73 | 6.39 |
| All | 0.75 | 0.52 | 409 | 668 | 93.1 | 29.2 | 2371 | 2523 | 1899 | 0.56 | 0.28 | 0.29 |

Table 2. Integral Parameters derived from average RSDs of each rain rate class and the whole dataset.

| R class | $Z$ (dBZ) | $D_m$ (mm) | log$_{10}$N$_v$ | $\sigma_M$ (mm) | $\sigma_M/D_m$ | $N_0$ (m$^{-3}$ mm$^{-1/3}$) | $\mu$ (mm$^{-1}$) | $\Lambda$ (mm$^{-1}$) |
|---------|-----------|-------------|----------------|----------------|----------------|----------------|----------------|----------------|
| 0.1 ≤ $R < 1$ | 20.0 | 0.73 | 4.15 | 0.44 | 0.60 | 1775 | −1.25 | 3.52 |
| 1 ≤ $R < 5$ | 30.9 | 1.14 | 3.92 | 0.67 | 0.59 | 2326 | −1.11 | 2.44 |
| 5 ≤ $R < 10$ | 38.1 | 1.55 | 3.77 | 0.86 | 0.56 | 3287 | −0.76 | 2.07 |
| 10 ≤ $R < 100$ | 47.5 | 2.14 | 3.71 | 1.28 | 0.60 | 3366 | −1.22 | 1.32 |
| $R ≥ 100$ | 58.3 | 2.97 | 3.82 | 1.82 | 0.61 | 7653 | −1.33 | 0.96 |
| All | 39.6 | 1.78 | 3.37 | 1.20 | 0.67 | 721 | −1.79 | 1.20 |
convective rains, two classification schemes were considered, namely, the T01 scheme (Testud et al. 2001) and the B03 scheme (Bringi et al. 2003). For a rain rate time series \( \{ R_i \} \), in the T01 scheme, if \( R_k \) and adjacent 10 spectra \( (R_k-5 \leq R_k \leq R_k+5) \) are all less than 10 mm h\(^{-1}\), then the spectrum \( k \) will be classified as stratiform; otherwise, the spectrum \( k \) will be classified as convective. As to the B03 scheme, if the standard deviation \( \sigma_R \) of 10 consecutive spectra is no larger than \( 1.5 \) mm h\(^{-1}\), then the 10 consecutive spectra will be classified as stratiform, whereas when the \( \sigma_R \) is larger than \( 1.5 \) mm h\(^{-1}\) and the rain rate is no smaller than \( 5 \) mm h\(^{-1}\), the spectrum will be classified as convective.

For the entire dataset (42,474 RSD samples), 33,518 (78.9 %) samples were classified as stratiform and 8956 (21.1 %) samples were classified as convective rain according to the T01 scheme. Using the B03 scheme, 30,127 (70.9 %) samples were classified as stratiform and 7866 (18.5 %) samples were classified as convective. T01 is a proper way to classify all samples to stratiform or convective rain, but the B03 scheme allows a higher rain rate to be classified as stratiform rain. The convective sample ratios for the stratiform samples were 26.1 % and 26.7 % for the T01 and B03 schemes, respectively, which were almost the same.

Figure 6 displays the distributions of \( D_m \) frequency for \( D_m \) (a) and \( \log_{10} N_w \) (b). Gray shades, blue/red lines, and cyan/magenta lines represent the entire dataset, stratiform rains classified by the T01 and B03 scheme, and convective rains classified by the T01 and B03 scheme, respectively. For the entire dataset (42,474 RSD samples), 33,518 (78.9 %) samples were classified as stratiform and 8956 (21.1 %) samples were classified as convective rain according to the T01 scheme. Using the B03 scheme, 30,127 (70.9 %) samples were classified as stratiform and 7866 (18.5 %) samples were classified as convective. T01 is a proper way to classify all samples to stratiform or convective rain, but the B03 scheme allows a higher rain rate to be classified as stratiform rain. The convective sample ratios for the stratiform samples were 26.1 % and 26.7 % for the T01 and B03 schemes, respectively, which were almost the same.

Figure 6 displays the distributions of \( D_m \) and \( \log_{10} N_w \) frequency of stratiform and convective RSD samples. For the entire dataset, the frequency of \( D_m \) peaks at 0.5–0.6 mm and 1.0–1.1 mm and the mean value, standard deviation, and skewness for \( D_m \) are 1.20 mm, 0.57 mm, and 1.03, respectively. Compared with the results of Chen et al. (2013) and Bringi et al. (2006), the mean \( D_m \) is smaller, whereas the standard deviation and skewness are larger in Mount Lushan. For \( \log_{10} N_w \), the peaks are 3.5–3.6 and 5.0–5.1, and the mean value, standard deviation, and skewness are 3.88, 0.80, and 0.74, respectively. The mean \( \log_{10} N_w \), which is close to the Marshall–Palmer value (8000 m\(^{-3}\) m\(^{-1}\) for \( N_w \)), is similar to Chen et al. (2013), but has a higher standard deviation and skewness. The bimodal distribution of \( D_m \) frequency was reported by Wen et al. (2016) and is caused by shallow rain. Furthermore, the frequency of \( \log_{10} N_w \) exhibits a second peak. This was also reported and attributed to shallow rain by Wen et al. (2016) and Fu et al. (2020). In the present study, the elevation of Mount Lushan will result in insufficient coalescence and thus, reduce the concentration of large raindrops. Also, it is easier for precipitating clouds to reach the ground because of the elevation, lack of evaporation in a saturated environment will increase the concentration of small raindrops. Hence, the second peak of \( \log_{10} N_w \) in Mount Lushan can be affected jointly by shallow rain and the elevation of mountain topography. Moreover, the first peak in the present study differs from some Meiyu studies (Fu et al. 2020; Wen et al. 2016). The higher standard deviation and skewness also indicate significantly higher RSD variability in Mount Lushan during the Meiyu season.
b. Distributions of $D_m$ and $\log_{10} N_w$ in stratiform and convective rains

The stratiform–convective rain type classification methods of T01 and B03 were compared (Fig. 6), and the frequencies of $D_m$ and $\log_{10} N_w$ for stratiform and convective rains of both methods exhibit similar results. The average value, standard deviation, and skewness of $D_m$ of T01/B03 methods are $1.04/1.02$ mm, $0.44/0.49$ mm, $1.04/1.02$, and $1.77/1.87$ mm, $0.61/0.58$ mm, $0.96/1.23$ for stratiform and convective rains, respectively. For $\log_{10} N_w$, the average value, standard deviation, and skewness of T01/B03 methods are $3.91/3.93$, $0.86/0.88$, $0.70/0.70$, and $3.76/3.77$, $0.52/0.49$, $-0.24/-0.24$ for stratiform and convective rains, respectively. There is no essential difference between the two methods; however, the B03 scheme displays more distinct stratiform/convective characteristics. Thus, here, the B03 scheme is considered as the classification method.

The difference between the stratiform and convective rains mainly manifests in the different peaks of the frequency distributions for $D_m$ and $\log_{10} N_w$. However, different peaks and skewness of frequency distributions for $D_m$ and $\log_{10} N_w$ have been found among different geographical locations (Bringi et al. 2006; Chen et al. 2013; Fu et al. 2020; Wen et al. 2016) in both stratiform and convective rains. Larger standard deviations for $D_m$ and $\log_{10} N_w$ were obtained, indicating a more notable variety of RSD in Mount Lushan during the Meiyu season because of the mountainous topography.

The distribution between $D_m$ and $\log_{10} N_w$ exhibits characteristics similar to those of other Meiyu RSD studies along the Yangtze River Valley (Fig. 7) (Chen et al. 2013; Fu et al. 2020; Wen et al. 2016), which is generally more stratiform-like. Compared with other Meiyu researches, there are more samples with larger $\log_{10} N_w$ and lower $D_m$ values in the Mount Lushan dataset (Bringi et al. 2003; Chen et al. 2013; Fu et al. 2020; Wen et al. 2016). A larger standard deviation of $\log_{10} N_w$ for stratiform rain and a smaller standard deviation of $D_m$ for convective rain were found in the present study, but the mean $\log_{10} N_w$ values were quite close. Compared with other related Meiyu precipitation studies (Chen et al. 2013; Fu et al. 2020; Wen et al. 2016), the present study obtained a smaller mean $D_m$ for stratiform rain but a larger mean $D_m$ for convective rain, indicating that the variety of $D_m$ is larger in Mount Lushan. For the mean $D_m$–$\log_{10} N_w$ pairs of all data in each study, all studies are similar and fall along the stratiform rain line proposed by Bringi et al. (2003) in the $D_m$–$\log_{10} N_w$ coordinate. No significant tendency for maritime or continental characteristics can be found in the Meiyu precipitation (Bringi et al. 2003, 2009; Thompson et al. 2015).

The relationship between $D_m$–$R$ and $N_w$–$R$ was investigated (Fig. 8). $D_m$ increases with rain rate for both stratiform and convective rains, and the power fitting results show little difference between the two rain types, which is similar to other Meiyu observations (Chen et al. 2013; Fu et al. 2020). The exponential fitting coefficients are higher than those of Bringi et al. (2013) and Wen et al. (2016), indicating that $D_m$ increases faster with $R$ at higher rain rates. The $N_w$ of stratiform rains shows little variation with rain rate,
whereas for convective rains, \( N_w \) shows a rising trend at lower rain rates. Compared with other studies, the exponential fitting coefficients in the present study are quite low (Chen et al. 2013; Fu et al. 2020; Wen et al. 2016), particularly for stratiform rains.

\( D_m \) and \( N_w \) both show bimodal type distributions (Figs. 8a, b), which correspond to the frequency distributions of stratiform rains (Fig. 6). The high \( N_w \) peak (Fig. 8a) corresponds to the low \( D_m \) peak (Fig. 8b). To investigate the unique high \( N_w \) samples, a subset consisting of samples with \( \log_{10}N_w > 4.5 \), was evaluated from stratiform rains for further analysis (Figs. 8a, b). The exponential fitting coefficients of the subset between \( D_m \) and \( R \) are the same as those of stratiform rain but with a lower primary coefficient, and \( N_w \) shows little variation with \( R \).

The average spectra of the subset of \( \log_{10}N_w > 4.5 \), \( \log_{10}N_w < 4.5 \), and the entire stratiform rain are presented in Fig. 9. The concentrations of smaller/larger (divided by 0.875 mm) for the subset with \( \log_{10}N_w > 4.5 \) are higher/lower than those of \( \log_{10}N_w < 4.5 \), and the subset with \( \log_{10}N_w > 4.5 \), has a narrower spectrum width. Rosenfeld and Ulbrich (2003) summarized the processes that can modify the shape of RSD.
and stated that typically, coalescence and evaporation cause a decrease in small raindrops. For the samples with $N_w > 4.5$, the narrow spectrum width and high small raindrop concentrations are the result of a lack of coalescence. When precipitation occurs within a cloud, the RSD spectra will always be narrow and with high concentrations for small raindrops because of insufficient coalescence and the absence of evaporation. This type of precipitation is frequently seen in Mount Lushan, and therefore, it can be assumed that the high-$N_w$ subset is the result of in-cloud precipitation.

c. RSD spectra

The average spectrum of convective rain shows higher concentrations than stratiform rain, whereas the differential concentrations rise with diameter (Fig. 10) (Table 3). Compared with other studies conducted at lower altitudes along the Yangtze River Valley (Chen et al. 2013; Fu et al. 2020), the concentrations of raindrops in Mount Lushan are higher at the small diameter end than particle size velocity (Parsivel) measurements, and this can be attributed to raw particle size and fall velocity distribution differences estimated by two sensors (Angulo-Martínez et al. 2018, see in Table 4). Furthermore, compared with Chen et al. (2013) and Wen et al. (2016), higher raindrop concentrations at the large-diameter end were also obtained in Mount Lushan and may be related to the mountainous topography.

The gamma distribution fits quite well for both rain types, except for the underestimation of the first diameter bin class (Fig. 10). The $N_0$ and $\mu$ for stratiform rains are higher than convective rains, and the $\Lambda$ for stratiform rains is smaller than convective rains. Compared with Chen et al. (2013), $N_0$, $\mu$, and $\Lambda$ are significantly lower in Mount Lushan, and $\mu$ is negative for both rain types, indicating that the spectra are bent toward the left bottom. The differences between the present study and those of Chen et al. (2013) can be attributed to the high concentration of small raindrops resulting from the mountainous topography of Mount Lushan.

3.3 Relationships of gamma distribution parameters

Theoretical calculations and observational results both show that the parameters of gamma distribution are not independent (Atlas et al. 1973; Chandrasekar and Bringi 1987; Chen, B. et al. 2017; Haddad et al. 1996; Seela et al. 2018; Ulbrich 1983; Zhang et al. 2003). To investigate the relationships between the
gamma distribution parameters and the distinctiveness of RSD in Mount Lushan, the relationships between \( \mu-N_0 \) and \( \mu-\Lambda \) were analyzed (Fig. 11).

It has been found theoretically and empirically that \( N_0 \) and \( \mu \) have an exponential relationship of \( N_0 = C_\nu \exp(3.2\mu) \), where \( C_\nu \) is a constant (Ulbrich 1983). The distributions of the two parameters show an obvious exponential relationship, and the fitting equations for stratiform rain, convective rain, and the entire dataset are \( N_0 = 3720 \exp(1.70\mu) \), \( N_0 = 7406 \exp(1.29\mu) \), \( N_0 = 13043 \exp(1.45\mu) \), respectively (Fig. 11). Compared with Ulbrich (1983), the present study shows a lower exponential coefficient, but the \( C_\nu \) here is of the same order of magnitude. However, when compared with the dataset on the Tibetan Plateau (Chen, B. et al. 2017), the exponential coefficient is similar, but a higher \( C_\nu \) was found in Mount Lushan. The differences between the three studies indicate that although \( \mu-N_0 \) has an exponential relationship, the fitting results vary significantly among different regions and rain types, and it is inconvenient to assess the varieties because \( N_0 \) will change with \( \mu \) (Chen, B. et al. 2017).

Zhang et al. (2001) and Zhang et al. (2003) proposed a quadratic polynomial \( \mu-\Lambda \) relationship \( (\Lambda = 0.0365\mu^2 + 0.735\mu + 1.935) \), which is thought to be a fundamental property of RSD, especially in convective rain (Seifert 2005). The \( \mu-\Lambda \) relationship varies according to geographic location, climate regime, and synoptic system (Bringi et al. 2003; Chen et al. 2011; Chen, B. et al. 2013, 2016, 2017; Ji et al. 2019; Luo et al. 2020). The \( \mu-\Lambda \) relationship for stratiform rain, convective rain, and the entire dataset of this study are presented in Fig. 11b. The fitting equations for three datasets are \( \Lambda = 0.0211\mu^2 + 1.365\mu + 2.374, \Lambda = 0.0533\mu^2 + 0.974\mu + 2.281, \) and \( \Lambda = 0.0347\mu^2 + 1.180\mu + 2.495 \), respectively. The \( \mu-\Lambda \) relationship varies similar to the results in the Tibetan Plateau, which is \( \Lambda = 0.0217\mu^2 + 1.090\mu + 1.706 \), but with a higher constant coefficient (Chen, B. et al. 2017). The \( \mu-\Lambda \) of convective rain in Mount Lushan is similar to the result of a squall line case in eastern China, which is \( \Lambda = 0.0585\mu^2 + 0.812\mu + 1.934 \), also with a higher constant coefficient (Chen et al. 2016). Compared with the results of Zhang et al. (2003), the quadratic coefficient for the entire dataset here is similar, but the primary and constant coefficients are higher. However, in Chen et al. (2013), which is \( \Lambda = 0.0149\mu^2 + 0.491\mu + 2.015 \), all coefficients differ from Mount Lushan. The present study shows that under conditions using different instruments, the similarities of the \( \mu-\Lambda \) relationship can still be assessed for different geophysical locations, climate regimes, and synoptic systems.

### 3.4 \( Z-R \) relationship

The \( Z-R \) relationship, in the form of \( Z = AR^b \) is an important criterion in radar QPE (Chen et al. 2013; Porcù et al. 2014; Tokay and Short 1996), and here, the \( Z-R \) relationship in Mount Lushan was investigated (Fig. 12). The \( Z-R \) relationship for the entire dataset is \( Z = 203R^{1.59} \) (Fig. 12a), which is similar to the continental stratiform rain \( Z = 200R^{1.6} \) (Marshall and Palmer 1948), and indicates that the Meiyu precipitation in Mount Lushan is typically stratiform-like. The \( Z-R \) relationships for stratiform and convective rains are \( Z = 194R^{1.35} \) and \( Z = 198R^{1.6} \), respectively, which are also similar to those of stratiform rain, although there are minute differences (Marshall and Palmer 1948). When comparing the operational WSR-88D...
Fig. 11. Scatterplots of $\mu-N_0$ (a) and $\mu-\Lambda$ (b) for stratiform (blue dots) and convective (orange dots) rains. The blue, red, and black solid lines indicate the exponential (a) and quadratic polynomial (b) fitting results of $\mu-N_0$ and $\mu-\Lambda$ relationship for stratiform rains (S), convective rains (C), and the entire dataset (A). The fitting equations are also presented inside the diagrams. The black dashed line in (b) shows the $\mu-\Lambda$ fitting equation of Zhang et al. (2003), which is $\Lambda = 0.0365 \mu^2 + 0.735 \mu + 1.935$. All the data in Fig. 11 were filtered using the standard of $N_t > 1000$ m$^{-3}$ and $R > 5$ mm h$^{-1}$ (Zhang et al. 2003).

Fig. 12. $Z-R$ scatterplots and fitting results for the Meiyu season at Mount Lushan: (a) the blue and orange scatterplots represent the samples with $\log_{10}N_w < 4.5$ and $\log_{10}N_w > 4.5$ in the entire dataset and the power fitting results of samples with $\log_{10}N_w < 4.5$, $\log_{10}N_w > 4.5$, and the entire dataset are presented by red, blue, and magenta lines; (b) the blue and orange scatterplots indicate the stratiform and convective samples. Among the blue scatterplots, the light/deep blue color represents the samples with $\log_{10}N_w > 4.5$ $\log_{10}N_w < 4.5$. The red line, blue solid line, blue dash dotted line, and blue dotted line show the power fitting results of each dataset. The dash, dash dotted, and dotted black lines indicate the power laws of stratiform rain $Z = 200R^{1.5}$ (Marshall and Palmer 1948), operational WSR-88D $Z = 300R^{1.5}$ (Fulton et al. 1998), and Meiyu result in Eastern China $Z = 368R^{1.21}$ (Chen et al. 2013).
$Z = 300R^{1.4}$ (Fulton et al. 1998) and Meiyu results in eastern China $Z = 368R^{1.21}$ (Chen et al. 2013), the rain rate $R$ derived from $Z$ will be overestimated/underestimated at lower/higher rain rate ranges (dividing rain rate approximately 5–10 mm h$^{-1}$) in Mount Lushan. The Meiyu precipitation in Mount Lushan can be generally characterized as typical stratiform rain.

The samples with log$_{10}N_w > 4.5$ show significantly different characteristics, and therefore, the differences between samples with log$_{10}N_w > 4.5$ and log$_{10}N_w < 4.5$ were investigated. The $Z$–$R$ scatterplots show a clear boundary between samples with log$_{10}N_w > 4.5$ and log$_{10}N_w < 4.5$, for the entire dataset (Fig. 12a) and the stratiform dataset (Fig. 12b). The $Z$–$R$ relationships of samples with log$_{10}N_w > 4.5$ for the entire dataset and stratiform rain dataset are $Z = 54R^{0.4}$ and $Z = 51R^{0.4}$, respectively, showing little difference. The characteristics of the spectra and $Z$–$R$ relationship for the high $N_w$ samples are similar to the shallow rains diagnosed by Wen et al. (2016), and were attributed to warm rain processes. For those with log$_{10}N_w < 4.5$, the $Z$–$R$ relationship for the entire dataset is $Z = 306R^{1.51}$, which is similar to that of WSR-88D (Fulton et al. 1998), but with a higher $b$ value. The $Z$–$R$ relationship for stratiform rain samples with log$_{10}N_w < 4.5$ is $Z = 203R^{2.59}$, which is very similar to continental stratiform rain (Marshall and Palmer 1948). The $Z$–$R$ relationship for the high-$N_w$ subset in the present study shows a higher rain rate at the same $Z$ value. Yuter and Houze (1997) reported a bimodally distributed $Z$–$R$ relationship in the Pacific Warm Pool, which corresponds to the populations of large and small drop spectra. The present study also revealed a similar bimodal distribution but with a significantly lower rain rate. The underlying reason should be further investigated.

4. Discussion

In Section 3, a typical dataset with high $N_w$ (log$_{10}N_w > 4.5$) was assessed and showed quite different RSD characteristics. To investigate the characteristics and underlying reasons for the high $N_w$ samples, a primary statistical analysis of the high $N_w$ subset was conducted. Approximately one-third (60) of the rain events had high $N_w$ samples with counts of more than 30. A further investigation of two long-lasting precipitation events of Meiyu found that high $N_w$ samples always existed within continuous long-lasting precipitation processes (Fig. 13) that both lasted for more than 1 day, with few interruptions. The high $N_w$ samples were normally obtained during the interval of two relatively heavy rain periods or in the dissipating period of the long-lasting precipitation (e.g., Figs. 13a, b). The samples with high $N_w$ can be characterized as follows: 1) high concentrations in the first two diameter classes, 2) narrow spectrum width (no larger than 1 mm), and 3) low but continuous rain rate (mostly lower than 5 mm h$^{-1}$).

Mount Lushan is well known for its changeable clouds and fogs, and it is believed that in-cloud precipitation is frequently observed on the observational platform (Fig. 14). When a rain event occurs within the cloud in Mount Lushan, the absence of evaporation will cause a high concentration of small raindrops, and the low clouds will also lack sufficient coalescence. As such, a narrow spectrum with a high small raindrop concentration will be expected from in-cloud rain. To confirm this, a rain case was observed by the LPM, fog monitor (DMT FM-100), and visibility meter (Vaisala PWD22) (Fig. 15). Under similar rain rates, the $N_w/D_m$ outside the cloud (before 09:00 on May 23, local solar time) was lower/higher than that inside the cloud (15:00–21:00 on May 23). When the rain began to dissipate, the $N_w/D_m$ became higher/lower. Wen et al. (2016) reported the shallow rain type during the Meiyu season, which is like the high $N_w$ subset and is regarded as forming through warm rain processes. However, in the present study, a more highlighted high $N_w$ subset can be derived from the entire dataset (e.g., Figs. 6, 12), indicating that in-cloud rain, which is highly related to mountainous topography, plays an important role in generating a high-$N_w$ RSD.

Although the topography of Mount Lushan is critical in generating in-cloud precipitation, to explain why the high-$N_w$ samples always occur in long-lasting precipitation, the underlying dynamics and thermodynamics must be investigated in depth. Furthermore, the microphysical mechanisms of conversion from cloud/fog droplets to raindrops and the interaction between cloud/fog and precipitation also require investigation.

5. Conclusions

Using the RSD data collected by LPM in Mount Lushan from 2016 to 2020, the RSD characteristics of Meiyu precipitation in Mount Lushan were studied. The special RSD samples with high $N_w$ were also discussed, and the results are as follows:

A dataset of 186 rain events was determined during the Meiyu season from 2016 to 2020 in Mount Lushan. For the entire dataset, lower rain rates (< 5 mm h$^{-1}$) contributed to the highest number of samples, whereas rain rates of 10–100 mm h$^{-1}$ contributed the highest precipitation amount. Extraordinarily high rain rates (> 100 mm h$^{-1}$) were found in Mount Lushan.
during the Meiyu season and contributed to quantitative precipitation (8.62 %) compared with its low frequency (0.32 %). For large-diameter ranges (> 0.5 mm), the concentrations for each diameter bin of the average spectra will increase with rain rate, whereas for small diameter ranges (< 0.5 mm), the concentrations for each diameter bin will rise only when the rain rates are higher (> 10 mm h⁻¹).

The performance of the two gamma fitting methods, namely, the ML and MM, were evaluated using the average spectra of each rain rate class for the Meiyu dataset. The ML method obtained better results for correlation coefficients and absolute biases, and the MM method obtained better results for relative biases and shapes of RSD. In simulating the RSD parameters, the MM method had good results for \( N_f \) and \( W \). Thus, the MM method achieved good results for simulating the Meiyu RSD in Mount Lushan.

Fig. 13. Two examples of precipitation processes with high \( N_w \) values. The first (a, b) is from 12:00 on June 28 to 07:40 on June 30, 2016, and the second is from 20:20 on July 15 to 06:00 July 17, 2019. The color maps and magenta lines in (a)/(c) represent the RSD and rain rate time series, and the blue and orange lines in (b)/(d) represent for the \( D_m \) and \( \log_{10}N_w \) time series.
The RSD parameters of \( N_T, W, Z, D_m, \) and \( \sigma_M \) increased with rain rate, whereas \( N_w \) and \( \sigma_M/D_m \) varied little with rain rate. For the gamma distribution parameters of the average spectra for different rain rates, \( N_0 \) and \( \Lambda \) rose/decreased with rain rate, and \( \mu \) had negative values for all rain rate classes. The gamma distribution for the average spectrum of the entire dataset was \( N(D) = 721D^{-1.79}e^{-1.20D} \). The frequency distributions of \( D_m \) and \( \log_{10} N_w \) both showed a special bimodal type. An exceptionally high-\( N_w \) (\( \log_{10} N_w > 4.5 \)) subset was diagnosed, which corresponds to the unique secondary peaks of \( D_m \) and \( \log_{10} N_w \), which has a narrower and steeper average spectrum with high concentrations for small raindrops (< 0.875 mm).

Two classification schemes (T01 and B03) for stratiform/convective rain were discussed, and the frequency distributions of \( D_m \) and \( \log_{10} N_w \) for stratiform and convective rains showed little difference between the two schemes. The distribution of \( D_m-\log_{10} N_w \)

![Fig. 14. An example of in-cloud precipitation (taken on August 12, 2020).](image)

![Fig. 15. (a) and (b) are the same as Fig. 13, but for the precipitation process from 00:00 May 23 to 16:00 on May 24, 2017, (c) shows the time series of drop size distributions from the fog monitor (color maps) and visibility (magenta line).](image)
showed differences between the two rain types and no significant maritime/continental characteristics. The $D_m – R$ and $N_w – R$ relationships showed little difference between stratiform and convective rains, and $N_w$ showed little variation with rain rate. The average spectra for stratiform and convective rains both had high concentrations of small raindrops, but the convective rains had larger raindrops. The gamma distribution parameters were also calculated (Table 3).

The relationships between the gamma distribution parameters of $\mu – N_0$ and $\mu – \Lambda$ for stratiform and convective rains were examined. The $\mu – N_0$ showed quite different characteristics for stratiform and convective rains, and the fitting equation for the entire dataset was $N_0 = 13043 \exp(1.45\mu)$. The Meiyu dataset of Mount Lushan showed a similar $\mu – \Lambda$ relationship ($\Lambda = 0.0347\mu^2 + 1.180\mu + 2.495$) to other studies, but in the present study, the lower $\mu$ values resulted in higher primary and constant coefficients in the quadratic polynomial fitting results.

The $Z – R$ relationship for the Meiyu season in Mount Lushan showed featured stratiform rain characteristics with $a Z = 203R^{0.59}$ fitting result. The $Z – R$ relationships for stratiform and convective rains showed little difference, but the dataset of high $N_w$ samples obtained a unique fitting result of $Z = 54R^{0.47}$.

The high-$N_w$ subset was normally detected in long-lasting precipitation during the Meiyu season. The RSD can be characterized as high concentrations in the first two diameter classes, with narrow spectrum width ($< 1$ mm), and low but continuous rain rate ($< 5$ mm h$^{-1}$). Further investigations demonstrated that these samples can be attributed to in-cloud precipitation, which is related to the mountainous topography of Mount Lushan.

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