Microphysical Characteristics of Winter Precipitation in Eastern China from 2014 to 2019

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Received: 18 February 2020; Accepted: 20 March 2020; Published: 24 March 2020

Abstract: To improve solid precipitation monitoring in the hydrology and meteorology field, 1-min precipitation data observed by the PARticle SIze VElocity (PARSIVEL) disdrometer in Nanjing, eastern China, from February 2014 to February 2019 for all days with solid precipitation, were used to study the microphysical characteristics of winter precipitation. In this study, the empirical V-D (velocity–diameter) relationships and observed surface temperature are used for matching precipitation types, and the precipitation data are divided into rain, graupel, wet snow and dry snow. The results show that dry snow and wet snow have maximum $D_m$ (mass-weighted mean diameter) and minimum $\log_{10} N_w$ (normalized intercept parameter), while rain shows the opposite. Additionally, the $\mu$-$\Lambda$ (shape parameter–slope parameter) curve of dry snow and wet snow is very close, and the $\mu$ value of dry snow and wet snow is higher than that of graupel and higher than that of rain for the same $\Lambda$ value. Furthermore, the $Z_e$-$S$ (equivalent reflectivity factor–precipitation intensity) relationships among different types of precipitation are significantly different. If only the $Z_e$-$S$ relationship of rain is used for quantitative precipitation estimation (QPE), then, for small precipitation intensity, solid precipitation will be overestimated, while, for large precipitation intensity, it will be underestimated.

Keywords: winter precipitation; particle size distribution; $\log_{10} N_w$-$D_m$; $\mu$-$\Lambda$; $Z_e$-$S$

1. Introduction

The accurate monitoring of solid precipitation is of great significance for aviation safety, transportation and freezing disaster prevention, especially in the middle and high latitudes [1–3]. Additionally, the study of the microphysical characteristics of solid precipitation contributes to the development of weather forecasts, remote sensing of precipitation, and hydrology [1,4–6]. The mass-size and velocity-size relationships of solid precipitation particles determine the correctness of Numerical Weather Prediction (NWP) model parameterization, which has an impact on the prediction of precipitation location, precipitation intensity and start and end times [7–9]. Whether passive or active, ground-based or space-based electromagnetic propagation models are sensitive to the shape and density of solid precipitation particles, and a reasonable description of precipitation microphysical characteristics is essential to the inversion algorithm of precipitation intensity based on remote sensing [10–12]. The erosion effect of precipitation on soil is closely related to its type and the particle size distribution (PSD), which is very important for the flood control and water fixation abilities of ecosystems [13–15].

Previous studies have been conducted on the microphysical characteristics of solid precipitation. Barthazy et al. [16] calibrated the Hydrometeor Velocity and Shape Detector (HVSD) instrument.
and measured the fall speed, shape and PSD of snowflakes. Zhang et al. [17] observed several weather processes involving solid precipitation using a 2-dimensional video disdrometer (2DVD) and compared the theoretically calculated polarization variables with the radar-measured values to verify the effectiveness of the density correction algorithm in Oklahoma. Jia et al. [10] used a PArticle SIze VElocity (PARSIVEL) disdrometer and microscopic photography to analyze the fall velocity and PSD of rain, graupel, snow and mixed-phase precipitation particles in northern China.

With the development of measurement technology in recent years, observational experiments of solid precipitation microphysical characteristics have been carried out routinely. However, on the one hand, due to the great difference in the physical properties of different solid precipitation particles, it is still an urgent problem to invert solid precipitation by radar remote sensing [18–20], but on the other hand, the data collected by previous researchers were mostly limited by quantity; their statistical significance has yet be further verified, and experiments were rarely carried out in many regions of the world, such as East Asia. By distinguishing precipitation types in advance, the accuracy of the quantitative precipitation estimation (QPE) of the polarization radar can be improved [3,21]. By establishing a more accurate electromagnetic propagation model according to the specific solid precipitation type, the uncertainty of the inversion algorithm can be reduced [22]. In addition, due to differences in regional climate and other factors, conducting more local statistical experiments is also a powerful means of improving the remote sensing measurement of solid precipitation information.

To improve the application level of remote sensing for solid precipitation in eastern China, this study analyzes the microphysical characteristics of rain, graupel, dry snow and wet snow by using 6 years of winter PARSIVEL (first generation) observation data in Nanjing. The next section describes the data sources, parameter calculations, and precipitation classification methods. Section 3 presents the analysis of the differences among the microphysical characteristics of different types of precipitation. The research methods are discussed in Section 4. The final section includes the conclusion and summary.

2. Data and Method

2.1. Data Sources

In this study, winter precipitation data from February 2014 to February 2019, observed by an OTT PARSIVEL disdrometer [10,23] at a station (31.97° N, 118.81° E, 32 m above sea level) in Nanjing, eastern China, were used (as shown in Figure 1). Nanjing is located in the north subtropical monsoon climate zone, which has abundant precipitation every year from approximately mid-November into winter. The temperature difference between winter and summer is significant, and the annual minimum temperature can reach −13.1 °C. With complex weather systems and frequent natural disasters, the weather and climate characteristics of Nanjing are representative of eastern China [24]. The selected precipitation days are the days with non-liquid precipitation verified by PARSIVEL data. As shown in Table 1, a total of 29 precipitation days were identified. On these precipitation days, all 1-min precipitation data (22,386 samples) recorded by PARSIVEL were used for the statistical analysis in this study. In addition to disdrometer data, local 1-h ground temperature data for precipitation days are also used to distinguish between dry snow and wet snow (see Section 2.4).
Table 1. The precipitation days selected in this study. The corresponding ground temperature and precipitation time are also shown. The time used here is Beijing time, which is 8 h earlier than UTC.

| Year | Date | Historical Weather Observation                  | Ground Temperature (°C) | Precipitation Time               |
|------|------|------------------------------------------------|--------------------------|----------------------------------|
| 2014 | 0205 | Sleet/Small to moderate rain                    | 2–3                      | 02:30–23:59                     |
|      | 0207 | Sleet/Light snow                               | –3–2                     | 00:00–19:30                     |
|      | 0212 | Sleet/Moderate snow                            | 0–4                      | 20:30–23:59                     |
|      | 0213 | Sleet/Cloudy                                    | –1–4                     | 00:00–08:00                     |
|      | 0218 | Heavy snow/Light to moderate snow               | –3–2                     | 08:00–23:00                     |
| 2015 | 0305 | Sleet/Overcast                                 | 2–5                      | 13:00–16:00                     |
|      | 0111 | Small rain/Sleet                               | 0–6                      | 00:00–23:59                     |
|      | 0120 | Sleet/Moderate to heavy snow                   | 0–4                      | 19:30–23:59                     |
|      | 0124 | Overcast/Heavy snow                            | –1–3                     | 16:30–23:59                     |
|      | 0125 | Heavy snow to Snowstorm/Moderate snow          | –3–0                     | 00:00–23:59                     |
| 2016 | 0126 | Overcast/Light snow                            | –3–1                     | 00:00–03:00                     |
|      | 0127 | Light snow/Light snow                          | –2–1                     | 06:00–23:59                     |
|      | 0128 | Light snow/Overcast                            | –7–1                     | 00:00–14:30                     |
|      | 1208 | Overcast/Light snow                            | 0–2                      | No precipitation                |
|      | 1230 | Light snow/Light snow                          | –2–1                     | 12:00–23:00                     |
| 2017 | 0208 | Light snow/Overcast                            | –2–2                     | 00:00–23:30                     |
|      | 0104 | Snowstorm/Moderate snow                       | –1–1                     | 00:00–06:00/15:30–23:59         |
|      | 0107 | Light rain/Sleet                               | –1–4                     | 00:30–14:00                     |
|      | 0124 | Overcast/Heavy snow                            | –1–3                     | 16:30–23:59                     |
|      | 0125 | Heavy snow to Snowstorm/Moderate snow          | –3–0                     | 00:00–23:59                     |
| 2018 | 0126 | Overcast/Light snow                            | –3–1                     | 00:00–03:00                     |
|      | 0127 | Heavy snow to Snowstorm/Heavy snow             | –2–1                     | 06:00–23:59                     |
|      | 0128 | Light snow/Overcast                            | –7–1                     | 00:00–14:30                     |
|      | 1208 | Overcast/Light snow                            | 0–2                      | No precipitation                |
|      | 1230 | Light snow/Light snow                          | –2–1                     | 12:00–23:00                     |
| 2019 | 0129 | Heavy snow/Sleet                               | 0–2                      | 02:00–23:00                     |
|      | 0130 | Light rain/Sleet                               | 1–8                      | 00:00–08:00                     |
|      | 0131 | Light snow/Overcast                            | –3–4                     | 00:00–08:00                     |
|      | 0207 | Light rain/Moderate rain                       | 0–4                      | 00:00–09:00/23:00–23:59         |
|      | 0208 | Light snow/Moderate snow                       | –1–2                     | 00:00–05:30/18:00–23:59         |
|      | 0209 | Overcast/Overcast                              | –1–1                     | 00:00–05:00/13:30–22:00         |
|      | 0210 | Light snow/Overcast                            | –2–1                     | 06:00–17:00                     |
|      | 0221 | Light rain/Sleet                               | 2–7                      | 00:00–02:00/16:30–23:59         |
|      | 0222 | Sleet/Overcast                                 | –1–6                     | 00:00–13:00                     |

Compared with the data recorded by the PARSIVEL disdrometer, the weather observation of the date corresponding to the shadow part in the table was incorrect. Light snow was observed for December 8, 2018, but the instrument did not record any precipitation. No nonliquid precipitation was observed for February 7, 2019, but the instrument recorded nonliquid precipitation. No precipitation was observed for February 9, 2019, but the instrument recorded a long period of precipitation.
2.2. Quality Control

The PARSIVEL disdrometer determines the size of the precipitation particles by measuring the attenuation caused by precipitation particles across its laser beam and determines the fall speed of precipitation particles by recording the time when the laser beam is blocked [25]. The output data of the instrument is a matrix of 32 by 32: 32 bins with sizes ranging from 0.062 to 24.5 mm and 32 bins with speeds ranging from 0.05 to 20.5 m/s [26,27]. Because of its good cost performance, the instrument is widely used in the QPE of radar, soil erosion and weather modification [13,28,29]. However, due to the limitations of the device performance and built-in algorithm, quality control is required to obtain the best possible measurement results. Because of the low signal-to-noise ratio, data from the first two size bins are not used [30]. For every 1-min sample, if the number of precipitation particles is less than 10, the sample is excluded [27]. In addition, the sampling area is corrected as \((30 \text{ mm} - 0.5D_i) \times 180 \text{ mm}\) to remove the boundary effect [31]. The velocity outliers on each size bin are eliminated according to the 3\(\sigma\) criterion (small particles with high velocity caused by spatter, large particles with low velocity caused by overlap). Through quality control, a total of 21274 samples were obtained.

2.3. Calculation of Integral Parameters

The number concentration \(N(D_i)\) \((\text{m}^{-3} \text{ mm}^{-1})\), which refers to the number of precipitation particles per unit volume per unit diameter, can be expressed as follows

\[
N(D_i) = \sum_{j=3}^{32} \frac{C_{ij}}{V_j \cdot A \cdot t \cdot \Delta D_i}
\]

where \(D_i\) (mm) is the median of the \(i\)th size bin, \(t\) (s) is the sampling time (\(t = 60\) s in this study), \(A\) (mm\(^2\)) is the sampling cross section \((A = 54\) mm\(^2\) for OTT PARSIVEL disdrometer), \(V_j\) (m/s) is the median of the \(j\)th velocity bin, \(\Delta D_i\) (mm) is the width of \(i\)th size bin, and \(C_{ij}\) is the amount in \(i\)th size bin and \(j\)th velocity bin during sixty seconds. To better describe PSD, we need to fit it with appropriate functions. The commonly used function is the three-parameter gamma function due to its universality [10,32]

\[
N(D) = N_0 D^\mu \exp(-\Lambda D)
\]

where \(D\) (mm) is the precipitation particle diameter, \(N_0\) (\(\text{mm}^{-1}\mu\text{m}^{-3}\)) is the intercept parameter, \(\mu\) is the shape parameter, and \(\Lambda\) (\(\text{mm}^{-1}\)) is the slope parameter. These three parameters can be determined by the order moment method [33,34]. The \(n\)th moment of PSD can be defined as follows

\[
M_n = \sum_{i=3}^{32} D_i^n N(D_i) \Delta D_i
\]

The intercept parameter \(N_0\), shape parameter \(\mu\) and slope parameter \(\Lambda\) can be expressed as follows

\[
N_0 = \frac{\Lambda^{(\mu+4)} M_3}{\Gamma(\mu + 4)}
\]

\[
\mu = \frac{11G - 8 + \sqrt{G(G + 8)}}{2(1 - G)}
\]

\[
\Lambda = \frac{(\mu + 4) M_3}{M_4}
\]

where \(G = \frac{M_4^3}{M_2^4 M_6}\).
In addition, the normalized intercept parameter \( N_w \) and the mass-weighted mean diameter \( D_m \) are defined as follows [35]

\[
N_w = \frac{4^4}{\Gamma(4)} M^5_1 \rho_1^5
\]

\[
D_m = \frac{M_4}{M_3}
\]

(7)

(8)

The precipitation intensity \( S \) (mm h\(^{-1}\)) (liquid equivalent) can be calculated by the following formula

\[
S = \frac{6 \times 10^{-1}}{\rho_w A} \sum_{i=3}^{32} M(D_i) N(D_i) \Delta D_i
\]

(9)

where water density \( \rho_w = 1 \) g cm\(^{-3}\), and precipitation particle mass \( M(D_i) \) (mg) employs an empirical relationship from Locatelli and Hobbs [36] for solid precipitation (as shown in Table 2).

The equivalent reflectivity factor of ice particle \( Z_e \) can be expressed as follows

\[
Z_e = \frac{|K_i|^2}{|K_w|^2} \sum_{i=3}^{32} D_i^6 N(D_i) \Delta D_i
\]

(10)

where \( D_i \) (mm) is the equivalent ice sphere diameter and \( K_i \) and \( K_w \) are the dielectric constants for ice and water, respectively \((|K_i|^2 = 0.208 \text{ and } |K_w|^2 = 0.93 \text{ for the usual meteorological radar wavelength}) \) [37]. Assuming \( D_i \) corresponds to \( D_i' \), then we can obtain the following expression

\[
M(D_i) = M(D_i') = \frac{\pi}{6} \rho_i D_i^3
\]

(11)

where the ice density \( \rho_i = 0.9167 \) g/cm\(^3\). Equation (11) is substituted into Equation (10) to obtain the following Equation [11]

\[
Z_e = \frac{|K_i|^2}{|K_w|^2} \left( \frac{6}{\pi \rho_i} \right)^2 \sum_{i=1}^{32} M(D_i)^2 N(D_i) \Delta D_i
\]

(12)

### Table 2. Empirical relationships of \( V \) (m/s)-\( D \) (mm) and \( M \) (mg)-\( D \) (mm) for different types of precipitation. The empirical relationships of graupel and snow are derived from Locatelli and Hobbs [36]. The empirical relationships of rain are derived from Atlas et al. [38]. The sample number \( N \) of each precipitation type and the total number Sum of samples for each category are also shown.

| Categories | Precipitation Type | \( V-D \) | \( M-D \) | \( N \) | Sum |
|------------|--------------------|-----------|-----------|-------|-----|
| Rain | | | | | |
| Graupel | Lump graupel 1 | \( V = 1.16D^{0.46} \) | \( M = 0.042D^{0.5} \) | 142 | |
| | Lump graupel 2 | \( V = 1.30D^{0.66} \) | \( M = 0.078D^{0.7} \) | 13 | |
| | Lump graupel 3 | \( V = 1.50D^{0.37} \) | \( M = 0.140D^{0.7} \) | 7361 | 7521 |
| | Conical graupel | \( V = 1.20D^{0.65} \) | \( M = 0.073D^{0.6} \) | 4 | |
| | Hexagonal graupel | \( V = 1.10D^{0.37} \) | \( M = 0.044D^{0.3} \) | 1 | |
| Snow | Graupelike snow of lump type | \( V = 1.10D^{0.26} \) | \( M = 0.09D^{0.2} \) | 405 | |
| | Graupelike snow of hexagonal type | \( V = 0.86D^{0.25} \) | \( M = 0.021D^{0.4} \) | 94 | |
| | Densely rimed dendrites | \( V = 0.62D^{0.33} \) | \( M = 0.015D^{0.3} \) | 11 | |
| | Densely rimed radiating assemblages | \( V = 1.10D^{0.12} \) | \( M = 0.039D^{0.1} \) | 1872 | 2337 |
| | Unrimed side planes | \( V = 0.81D^{0.99} \) | - | 1 | |
| | Aggregates of unrimed radiating assemblages | \( V = 0.80D^{0.16} \) | \( M = 0.073D^{0.1} \) | 15 | |
| | Aggregates of densely rimed radiating assemblages of dendrites or dendrites | \( V = 0.79D^{0.27} \) | \( M = 0.037D^{0.1} \) | 18 | |
| | Aggregates of unrimed radiating assemblages of plates, side planes, bullets, and columns | \( V = 0.69D^{0.41} \) | \( M = 0.037D^{0.1} \) | 18 | |
| | Aggregates of unrimed side planes | \( V = 0.82D^{0.12} \) | \( M = 0.04D^{0.1} \) | 123 | |
2.4. Classification of Precipitation Types

Common methods for distinguishing precipitation types include using Formvar slides to collect particles and manually determine the types with a microscope [10,39–41] or automatically judging the precipitation particle pictures taken by combining with an image recognition algorithm [7,12]. In addition, because the $V-D$ relationships between different types of precipitation are obviously different, the $V-D$ function fitted by 1-min average data can also be used to distinguish precipitation types [11,42,43]. In this study, the $V_{fit} = aD^b$ relationship fitted with a 1-min sample (using the least square method) was matched with the 15 $V-D$ relationships in Table 2, and the type with the smallest difference was considered to be the type of the 1-min sample

$$\arg\min_x \sum_{i=3}^{32} \sum_{j=1}^{32} C_{ij}(V_{fit}(D_i) - V_x(D_i))^2$$ (13)

where $x$ refers to the 15 precipitation types in Table 2. Accumulated raw particle counts by size and velocity for every precipitation type are shown in Figure 2. Through this classification method, the numbers of 1-min samples of rain, graupel and snow are 11,196, 7521 and 2557, respectively.
Figure 2. Accumulated raw particle counts by size and velocity for 15 precipitation types and their corresponding V–D empirical relationship (blue lines) from Locatelli and Hobbs [36] and Atlas et al. [38].

Furthermore, depending on the temperature near the ground, snowfall may be divided into dry snow and wet snow, whose microphysical characteristics may vary greatly [2]. According to the ground temperature data recorded on 1 h time resolution, the snow samples obtained above are further divided into dry snow and wet snow. If the temperature \( t \geq 0 \) °C, the sample is considered to be wet snow; otherwise, it is considered to be dry snow. Finally, 2014 samples of dry snow and 545 samples of wet snow are obtained.

3. Results

3.1. The PSD of Different Types of Precipitation

Figure 3 shows the distribution of the mean particle concentrations of rain, graupel, wet snow and dry snow. The particles of the three types of solid precipitation (graupel, wet snow and dry snow) are much larger overall than those of rainfall. Raindrops larger than 6 mm in diameter have a concentration of less than \( 0.01 \) m\(^{-3}\) mm\(^{-1}\), but particles of three types of solid precipitation can exceed 13 mm in diameter at the same concentration. Among them, the size of wet snow particles is smaller than that of dry snow for the same concentration, which may be because when the temperature is above freezing, the volume of hydrometeors decreases due to the transformation from the solid to liquid phase. In addition, the concentration of wet snow is lower than that of graupel and dry snow at all diameters. The concentration of graupel is higher than that of dry snow for small hydrometeors (D < 1.625 mm) and is the opposite for large hydrometeors (D > 3.25 mm). Furthermore, wet snow and dry snow have the largest peak diameters (0.937 and 0.687 mm, respectively), followed by graupel (0.562 mm), then rain (0.437 mm), which is consistent with the conclusion of Jia et al. [10]. As shown in Table 3, the skewness and kurtosis of the PSD of the four types of precipitation are all positive. The PSD has a maximum skewness of 2.32 and a maximum kurtosis of 4.12 for rain (meaning that the proportion of hydrometeors greater than the peak diameter is the highest and hydrometeors are most concentrated at the peak diameter for rainfall), whereas the opposite is true for wet snow.

| Precipitation Type | Peak Diameter (mm) | Skewness | Kurtosis |
|--------------------|--------------------|----------|----------|
| Rain               | 0.437              | 2.32     | 4.12     |
| Graupel            | 0.562              | 1.52     | 0.77     |
| Wet snow           | 0.937              | 1.23     | 0.06     |
| Dry snow           | 0.687              | 1.34     | 0.24     |
Unfortunately, due to the lack of previous studies on the microphysical characteristics of solid precipitation, the log10Nw-Dm of graupel, wet snow and dry snow in this study cannot be compared with the statistical results in other regions.

### Table 3. Peak diameters, skewness and kurtosis of particle size distribution (PSD) for different types of precipitation.

| Precipitation Type | Peak Diameter (mm) | Skewness | Kurtosis |
|--------------------|--------------------|----------|----------|
| Rain               | 0.437              | 2.32     | 4.12     |
| Graupel            | 0.562              | 1.52     | 0.77     |
| Wet snow           | 0.937              | 1.23     | 0.06     |
| Dry snow           | 0.687              | 1.34     | 0.24     |

#### 3.2. The log10Nw-Dm Distributions of Different Types of Precipitation

The normalized intercept parameter log10Nw and the mass-weighted mean diameter Dm directly reflect the concentration and size characteristics of precipitation particles, and their distribution is of great significance to the classification of precipitation types [27,28,33,44]. To study the differences in the microphysical characteristics of different types of precipitation in Nanjing, the statistical results of log10Nw versus Dm are shown in Figure 4. As seen from the figure, rain generally has the highest concentration and minimal size, while wet snow and dry snow have the lowest concentrations and maximum size. In addition, dry snow and wet snow have similar concentrations, but the particle size of dry snow is larger than that of wet snow (probably due to melting, as mentioned above). Furthermore, the Dm distribution of the three types of solid precipitation is much more widespread than that of rain, especially for dry snow.

The average log10Nw-Dm value of the rain is closer to the stratiform rain line (green dashed line) measured by Bringi et al. [28], which suggests that the winter rainfall in the Nanjing area mostly comes from the stratiform cloud system. The average log10Nw-Dm value of the three types of solid precipitation is closer to the continental convective rain area (black dashed rectangle), especially for graupel. The mean and standard deviation of specific log10Nw and Dm are shown in Table 4. Unfortunately, due to the lack of previous studies on the microphysical characteristics of solid precipitation, the log10Nw-Dm of graupel, wet snow and dry snow in this study cannot be compared with the statistical results in other regions.
Rain

Tang et al. [53], the \( \Lambda \) obtained in this study in the small snow and wet snow in the interval of 5 snow is greater than that of graupel and greater than that of rain. In addition, the \( \mu \) by the least square method. As seen from the figure, for the same \( \Lambda \) heavily influenced by the microphysical characteristics of precipitation [27,51]. Thus, a localized \( \mu \) their inversion often requires certain constraints on the parameters. It is common to assume that the \( \mu \)

Unfortunately, due to the lack of previous studies on the microphysical characteristics of solid precipitation comes from the stratiform cloud system. The average \( \log_{10} \) of four types of precipitation; and (c) The probability–density curves of \( \log_{10}N_{w} \) of four types of precipitation.

Table 4. The mean (ME) and standard deviation (SD) of \( \log_{10}N_{0}, \mu, \Lambda, \log_{10}N_{w}, D_{m}, S \) and \( Z_{e} \) for different types of precipitation.

| Precipitation Type | \( \log_{10}N_{0} \) (mm\(^{-1}\)m\(^{-3}\)) | \( \mu \) | \( \Lambda \) (mm) | \( \log_{10}N_{w} \) (mm\(^{-1}\)m\(^{-3}\)) | \( D_{m} \) (mm) | \( S \) (mm h\(^{-1}\)) | \( Z_{e} \) (dBZ) |
|--------------------|---------------------------------|------|---------------|----------------|----------------|----------------|----------------|
| Rain               | 7.86                           | 4.47 | 7.58          | 6.35            | 15.53          | 12.43          | 3.41           | 2.73           | 0.73           | 2.55           | 9.58           | 11.01          |
| Graupel            | 4.22                           | 2.72 | 2.90          | 4.98            | 4.53           | 6.71           | 3.30           | 0.53           | 2.58           | 1.25           | 2.07           | 2.93           | 23.40          | 13.87          |
| Wet snow           | 3.59                           | 2.38 | 4.79          | 4.49            | 4.37           | 4.87           | 2.95           | 0.49           | 3.17           | 1.78           | 0.16           | 0.20           | 6.83           | 9.89           |
| Dry snow           | 2.90                           | 2.64 | 4.10          | 5.38            | 3.21           | 3.59           | 2.99           | 0.63           | 3.49           | 2.00           | 0.27           | 0.40           | 9.67           | 8.89           |

3.3. The \( \mu–\Lambda \) Relationships among Different Types of Precipitation

The three-parameter gamma function described in Equation (2) is widely used in fields such as ground-based or space-based remote sensing, numerical weather prediction and microwave communication [1,45–47]. However, since there are as many as three unknown parameters and usually only two data sources at most (such as dual-frequency radar on GPM [48] and ground-based radar [49]), their inversion often requires certain constraints on the parameters. It is common to assume that the shape parameter \( \mu \) is a constant [50]. However, it has been proven that \( \mu \) is highly variable, and it is heavily influenced by the microphysical characteristics of precipitation [27,51]. Thus, a localized \( \mu–\Lambda \) relationship is proposed to reduce the number of required inversion parameters [29,44,52,53].

Figure 5 shows the \( \mu–\Lambda \) scatters of the four types of precipitation and their fitting curves obtained by the least square method. As seen from the figure, for the same \( \Lambda \), the \( \mu \) value of dry snow and wet snow is greater than that of graupel and greater than that of rain. In addition, the \( \mu–\Lambda \) curves of dry snow and wet snow in the interval of 5 < \( \Lambda \) < 25 are close to coincidental. Furthermore, excluding Tang et al. [53], the \( \mu–\Lambda \) relationship of rain from previous studies is very close to the \( \mu–\Lambda \) relationship obtained in this study in the small \( \Lambda \) value region (\( \Lambda < 15 \)), especially that obtained by Wen et al. [44],
whose dataset also comes from the winter rain in Nanjing between 2014 and 2016. The parameter values of the $\mu$–$\Lambda$ relationship of each type of precipitation in this study and previous studies are shown in Table 5. Additionally, due to the lack of research on the $\mu$–$\Lambda$ relationship of solid precipitation, the $\mu$–$\Lambda$ relationship of graupel, dry snow and wet snow obtained in this study is difficult to compare with other studies.

![Figure 5](image)

**Figure 5.** The scatter distributions of $\mu$–$\Lambda$ (gray triangle, asterisk, cross, square) and $\mu$–$\Lambda$ fitted functions (yellow, cyan, wet snow and dry snow solid lines) of rain, graupel, wet snow and dry snow, respectively. The four dashed lines are derived from the $\mu$–$\Lambda$ relationship calculated by predecessors. The details are shown in Table 5.

**Table 5.** The $\mu$–$\Lambda$ relationships among different types of precipitation and previous studies.

| Precipitation Type | Site                  | Time                  | $\mu$–$\Lambda$            |
|--------------------|-----------------------|-----------------------|----------------------------|
| Rain               | Nanjing, East China   | Winter from Feb 2014  | $\mu = -0.0074\Lambda^2 + 0.7564\Lambda - 1.5520$ |
| Graupel            |                       | to Feb 2019           | $\mu = -0.0073\Lambda^2 + 0.8340\Lambda - 0.7664$ |
| Wet snow           | Nanjing, East China   | 2014 to 2016          | $\mu = -0.0066\Lambda^2 + 0.8688\Lambda + 0.8648$ |
| Dry snow           | Nanjing, East China   | Winter from Feb 2014  | $\mu = -0.0106\Lambda^2 + 0.9936\Lambda - 0.0820$ |
| Winter rain (Wen et al. [44]) | Nanjing, East China | 2014 to 2016          | $\mu = -0.0110\Lambda^2 + 0.8210\Lambda - 2.3700$ |
| Rain (Zhang et al. [54]) | Florida, America    | Summer of 1998        | $\mu = -0.0210\Lambda^2 + 0.9880\Lambda - 2.6690$ |
| Rain (Cao et al. [32]) | Oklahoma, America    | 2005 to 2007          | $\mu = -0.0201\Lambda^2 + 0.9020\Lambda - 1.7180$ |
| Rain (Tang et al. [53]) | Beijing, North China | Jul to Oct 2008       | $\Lambda = 0.0075\mu^2 + 0.7230\mu + 1.1721$ |

### 3.4. The $Z_e$–$S$ Relationships among Different Types of Precipitation

The $Z$–$S$ relationship is mainly used for the QPE of weather radar [27,55]. However, instead of the reflectivity factor $Z$, weather radar actually measures the equivalent reflectivity factor $Z_e$. For rain, the equivalent reflectivity factor $Z_e$ is equal to the reflectivity factor $Z$, because the raindrops are small and nearly spherical [37]. Nevertheless, for snow particles or graupel particles, due to their large size and complex shape, the above approximation is obviously not applicable [37]. Through calculation, it can be obtained that $Z_e = 0.189Z$ if the size of the hydrometeors is expressed as the equivalent ice sphere diameter [2].

Figure 6 shows the $Z_e$–$S$ relationship fitted in this study and in previous studies. It should be mentioned that most of the previous results showed a $Z$–$S$ relationship. For the convenience of comparison, $Z_e = 0.189Z$ is used to convert this relationship into a $Z_e$–$S$ relationship. Table 6 records these specific parameters. As illustrated in this figure, when $S > 1.1$ mm h$^{-1}$, for the same $Z_e$, the precipitation intensity of dry snow is greater than that of graupel and wet snow, and greater than that of rain. The $Z_e$–$S$ relationships between graupel and wet snow are the closest, especially for the large precipitation intensity range ($S > 10$ mm h$^{-1}$). For small precipitation intensities ($S <$
0.2 mm h\(^{-1}\)), the equivalent reflectivity factor of dry snow is greater than that of wet snow, followed by graupel, and then rain for the same \(S\). This means that if the \(Z_e-S\) relationship of rain is uniformly used for the inversion of \(S\), for heavy precipitation, the \(S\) of solid precipitation will be underestimated, while, for weak precipitation, the \(S\) of solid precipitation will be overestimated.

![Figure 6](image-url)  
**Figure 6.** The scatter distributions of \(Z_e-S\) (gray triangle, asterisk, cross, square) and \(Z_e-S\) fitted functions (yellow, cyan, red and blue solid lines) of rain, graupel, wet snow and dry snow, respectively. In addition, the \(Z_e-S\) relationships (dotted or dashed lines) from previous studies are shown in this figure. The details are shown in Table 6.

| Precipitation Type                  | \(Z_e-S\)  |
|-------------------------------------|-------------|
| Rain                                | \(Z_e = 3115^{2.34}\) |
| Graupel                             | \(Z_e = 2525^{3.03}\) |
| Wet snow                            | \(Z_e = 3945^{1.93}\) |
| Dry snow                            | \(Z_e = 1455^{3.33}\) |
| Graupel (Gray and Male [59])        | \(Z_e = 1705^{3.90}\) |
| Snow (Gunn and Marshall [58])       | \(Z_e = 3785^{5.00}\) |
| Wet snow (Imai 1960 [56])           | \(Z_e = 3975^{6.00}\) |
| Dry snow (Imai 1960 [56])           | \(Z_e = 1015^{5.00}\) |
| Snow (Sekon and Srivastava [18])    | \(Z_e = 3375^{5.21}\) |
| Wet snow (Puhakka [57])             | \(Z_e = 3025^{5.00}\) |
| Dry snow (Puhakka [57])             | \(Z_e = 1985^{5.00}\) |

The \(Z_e-S\) relationships of wet snow from Imai [56] and Puhakka [57] are very consistent with those of the wet snow fitted in this study. In addition, the \(Z_e-S\) relationship of snow from Gunn and Marshall [58] is also very similar to that of wet snow, while the \(Z_e-S\) relationship of snow from Sekon and Srivastava [18] seems to be more similar to that of rain in this study. Furthermore, the \(Z_e-S\) relationships of dry snow from Imai [56] and Puhakka [57] differ significantly from those of this study, especially for heavy precipitation intensity. The same is true for the \(Z_e-S\) relationships between graupel from Gray and Male [59] and graupel in this study.

### 4. Discussion

The principle of the precipitation classification method used in this study is that there are differences in the \(V-D\) relationships among different types of precipitation particles, which is also the method...
used by the PARSIVEL disdrometer to distinguish the precipitation types. Similarly, Yuter et al. [11] also studied the microphysical characteristics of coexisting rain and wet snow by distinguishing the V–D relationship differences. In addition, Jia et al. [10] analyzed the V–D relationships of raindrops, graupel particles and snowflakes and found that these particles largely depended on the fitted empirical function, indicating the reliability of using the V–D relationship to identify precipitation types. However, the fall velocity of precipitation particles fluctuates under the influence of vertical airflow. According to the differences in specific weather conditions, the empirical relationship may produce errors. In this regard, Niu et al. [32] used local air density to revise the actual fall velocity of precipitation particles to exclude the influence of airflow. Furthermore, fewer field experiments have resulted in fewer samples being available at present. For example, Locatelli and Hobbs [36] used only a few dozen datapoints to fit the V–D relationships, but they have been used in the parameterization of weather and climate models [7]. Therefore, it may be inappropriate to use the empirical relationships obtained by Locatelli and Hobbs to match the precipitation type.

The estimation method of PSD parameters also needs to be discussed. In this study, the estimation method of PSD parameters is the moment method without truncation. However, in practice, the estimation effects of truncation or no truncation, moment method, least square method or maximum likelihood method are different. Mallet and Barthes [60] carried out the simulation of different estimation methods considering noise measurements, the absence of small drops, size of the collecting area, and integration time. The results show that the estimation effect of the maximum likelihood method is better than the others. Hence, the estimation method of PSD parameters can be further improved. In addition, different time steps of classification also affect the observation results, which are 1-min in this study. Matching the type based on the V–D distribution obtained by too short a time step (meaning too few particles recorded in the time interval) will result in variability in the result, while matching the type based on the V–D distribution obtained by too long a time step (meaning too many particles recorded in the time interval) may cause the result to be wrong due to the smoothness.

The PSD data used in this study were measured by a PARSIVEL disdrometer. This instrument is widely used in the study of worldwide precipitation microphysical characteristics because of its high-cost performance and portability [29]. It was originally primarily developed as a PSD measurement of rainfall and can be used as a weather sensor to distinguish precipitation types [27]. Löffler-Mang and Joss [42] investigated the potential of a PARSIVEL disdrometer measuring the PSD of solid precipitation. By adjusting the mass–size relationship, the reflectivity factor of snow measured by PARSIVEL is in good agreement with the measured value of the C-band radar [61]. However, the greatest obstacle to using it to measure solid precipitation is the built-in algorithm based on the raindrop hypothesis. Since snowflakes tend to be asymmetrical, the PARSIVEL disdrometer may underestimate their size [10]. The velocity is also subject to error, as it is determined by the vertical size of the snowflake. In addition, the PARSIVEL disdrometer can only count in discrete velocities and size ranges, and the velocity and diameter values can only be represented by the median of each bin, resulting in a quantitative error. Moreover, due to the stickiness of snow particles, some abnormally large particles recorded also introduce errors, especially for wet snow.

There are other instruments that can be used to observe precipitation microphysical characteristics, but they also have their own shortcomings. For example, 2DVD can obtain the two-dimensional contour of precipitation particles, but it will underestimate the number of precipitation particles with diameters of less than 0.3 mm [29]; snowflake video imager (SVI) can record the image of snowflakes, but not their fall speeds [22]. To obtain more accurate measurement results, researchers are committed to developing new measurement methods and instruments, such as multiangle snow imager (MASC) [62], and precipitation microphysical characteristics sensor (PMCS) [63]. These advances will have an important impact on QPE, NWP and other fields.
5. Conclusions

In this study, the microphysical characteristics of winter precipitation in eastern China were analyzed by using the PARSIVEL disdrometer in Nanjing. The four precipitation types were classified and matched based on the $V$–$D$ relationship, and their PSD, $\mu$–$\Lambda$, $\log_{10}N_{w}$–$D_m$ and $Z_e$–$S$ values were also compared.

First, the spectrum of the three types of solid precipitation (graupel, wet snow and dry snow) is much wider than that of rain. For large particles, the concentration of dry snow is greater than that of graupel and greater than that of wet snow. For small particles, the concentration of graupel is greater than that of dry snow and greater than that of wet snow. Second, the size of the dry snow particles is larger than that of the wet snow particles, but the overall concentration is the same. Graupel has a smaller size and a larger number of particles, followed by rain. Moreover, the $\mu$–$\Lambda$ curves for dry snow and wet snow are very similar in the small $\Lambda$ region. In general, for the same $\Lambda$ value, the $\mu$ value of wet snow is greater than that of dry snow, followed by that of graupel, and finally rain. Furthermore, there are significant differences in the $Z_e$–$S$ relationships of different types of precipitation. If only the $Z_e$–$S$ relationship of rain is used for QPE, the intensity of heavy and light solid precipitation will be underestimated and overestimated, respectively.

With the invention of instruments using new principles and the continuous improvement of the existing instruments’ performances, the observation of the microphysical properties of precipitation has become increasingly accurate. In addition to PSD, researchers have even begun to study the three-dimensional shape, riming degree and density of precipitation particles. With a more accurate description of the microscopic properties of precipitation and a deeper understanding of the precipitation evolution process, existing parameterization schemes and radiation transmission models will be further improved, especially for polarization radar.

Author Contributions: Conceptualization, K.P. and X.L.; Data curation, X.L.; Funding acquisition, X.L. and Y.W.; Investigation, H.H. and Y.W.; Methodology, K.P.; Resources, X.L.; Supervision, X.L., H.H. and S.H.; Validation, K.P., X.L., Y.S. and S.H.; Visualization, K.P. and Y.S.; Writing—original draft, K.P.; Writing—review and editing, K.P. and X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (grant numbers 41975030, 41327003, and 41475020) and Scientific Research Projects of Nanjing Meteorological Bureau, China (grant number NJ201907).

Acknowledgments: The authors would like to express their gratitude to the three anonymous reviewers for their comments that improved this manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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