Improving Polarimetric C-Band Radar Rainfall Estimation with Two-Dimensional Video Disdrometer Observations in Eastern China

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ABSTRACT

In this study, the capability of using a C-band polarimetric Doppler radar and a two-dimensional video disdrometer (2DVD) to estimate monsoon-influenced summer rainfall during the Observation, Prediction and Analysis of Severe Convection of China (OPACC) field campaign in 2014 and 2015 in eastern China is investigated. Three different rainfall estimators, for reflectivity at horizontal polarization [$R(Z_h)$], for reflectivity at horizontal polarization and differential reflectivity factor [$R(Z_h, Z_{dr})$], and for specific differential phase [$R(K_{DP})$], are derived from 2-yr 2DVD observations of summer precipitation systems. The radar-estimated rainfall is compared to gauge observations from eight rainfall episodes. Results show that the two polarimetric estimators, $R(Z_h, Z_{dr})$ and $R(K_{DP})$, perform better than the traditional $Z_h$–$R$ relation [i.e., $R(Z_h)$]. The $K_{DP}$-based estimator [i.e., $R(K_{DP})$] produces the best rainfall accumulations. The radar rainfall estimators perform differently across the three organized convective systems (mei-yu rainband, typhoon rainband, and squall line). Estimator $R(Z_h)$ overestimates rainfall in the mei-yu rainband and squall line, and $R(Z_h, Z_{dr})$ mitigates the overestimation in the mei-yu rainband but has a large bias in the squall line. QPE from $R(K_{DP})$ is the most accurate among the three estimators, but it possesses a relatively large bias for the squall line compared to the mei-yu case. The high variability of drop size distribution (DSD) related to the precipitation microphysics in different types of rain is largely responsible for the case-dependent QPE performance using any single radar rainfall estimator. The squall line has a distinct ice-phase process with a large mean size of raindrops, while the mei-yu rainband and typhoon rainband are composed of smaller raindrops. Based on the statistical QPE error in the $Z_{DR}$–$Z_{DR}$ space, a new composite rainfall estimator is constructed by combining $R(Z_h)$, $R(Z_h, Z_{dr})$, and $R(K_{DP})$ and is proven to outperform any single rainfall estimator.

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1. Introduction

Polarimetric radar variables, such as differential reflectivity factor $Z_{DR}$, copolar cross correlation $\rho_{hv}$, differential phase $\phi_{DP}$, and specific differential phase $K_{DP}$, can provide information about the size, shape, and orientation of the precipitation particles. Quantitative precipitation estimation (QPE) algorithms using these polarimetric radar variables have been studied in the last two decades (Ryzhkov and Zrnić 1995, 1996; Brandes et al. 2001; Zhang et al. 2001; Ryzhkov et al. 2005a,b; Bringi et al. 2011; You et al. 2014b). Compared to conventional reflectivity-based QPE algorithms, polarimetric radar–based QPE techniques have advantages in several aspects (Zrnić and Ryzhkov 1996; Ryzhkov et al. 2005a). Including $Z_{dr}$ (linear form of $Z_{DR}$) in addition to equivalent reflectivity factor $Z_{b}$ (linear form of $Z_{H}$), rainfall estimated from the pair ($Z_{b}$, $Z_{dr}$) is less affected by the unknown drop size distribution (DSD) and can provide improved QPE results (Seliga and Bringi 1976; Aydin and Giridhar 1992; Zhang et al. 2001; Brandes et al. 2002; Lee 2006; Zhang et al. 2006; Cao et al. 2008, 2010; You et al. 2014b; Zhang 2016). Furthermore, $K_{DP}$-based QPE has the advantages of immunity/insensitivity to calibration errors, attenuation, partial beam blockage, and ground clutter (Ryzhkov and Zrnić 1995, 1996; Ryzhkov et al. 2005a). It was also found that $R(K_{DP})$ provides the most accurate estimation for heavy rain among many radar QPE methods, since $K_{DP}$ is proportional to the 4.24th moment of DSD that is closer to the 3.67th moment of DSD (related to rain rate) than the 6th moment ($Z_{b}$; Sachidananda and Zrnić 1986; Ryzhkov and Zrnić 1996; Brandes et al. 2001; Ryzhkov et al. 2005a). Polarimetric radar–based QPE algorithms have been studied extensively in the United States, Australia, and Europe and have now become a mature technology. However, there have been very few studies on the characteristics of the polarimetric radar–based QPE algorithms in China.

Therefore, it is important to further improve QPE performance within these weather systems for flood monitoring, urban waterlogging prediction, and water resource management in eastern China.

To improve the understanding of the dynamics and microphysics of severe convective systems, the Observation, Prediction and Analysis of Severe Convection of China (OPACC) field campaign was conducted in the Yangtze–Huaihe River basin in eastern China in the summers of 2014 and 2015. For the first time, a C-band polarimetric radar operated by Nanjing University of China (NJU-CPOL), a third-generation two-dimensional video disdrometer (2DVD; Schönhuber et al. 2007), and hundreds of tipping-bucket gauges operated by the China Meteorological Administration (CMA) were deployed together to observe the rainfall systems in eastern China (Fig. 1). In this study, rain rate and synthetic polarimetric radar variables are calculated from the 2DVD data collected during the summers of 2014 and 2015, from which the synthetic polarimetric radar parameters $Z_{H}$, $Z_{DR}$, and $K_{DP}$, and their corresponding rainfall estimators $R(Z_{b})$, $R(Z_{b}, Z_{dr})$, and $R(K_{DP})$, are derived to form the basis for rainfall estimation in this region using NJU-CPOL data. Gauge measurement in this study is regarded as the ground “truth” of rainfall to evaluate the performance of NJU-CPOL-derived QPE products.

There were 11 intensive observation periods (IOPs) during OPACC in the Yangtze–Huaihe River basin in eastern China in the summer of 2014. However, only eight IOPs with measurable precipitation within 100 km
of the NJU-CPOL (the black circle in Fig. 1) are used in this study (Table 1). Three different rainfall cases, including the mei-yu rainband, typhoon rainband, and squall line, are then selected to characterize QPE algorithms in these three types of precipitation systems.

The relationship between QPE performance and DSD variation in precipitation systems has been discussed (Ryzhkov et al. 2005a; Zhang 2016). It has been well documented that DSDs vary with respect to rain intensity, type, and season (Rosenfeld and Ulbrich 2003; Zhang et al. 2006), while the variability of DSDs can lead to uncertainties in the radar-based QPEs. On the other hand, the relationships of polarimetric radar variables can be used to characterize the variety of DSDs: the $Z_{DR}$ versus $Z_{H}$ pair is useful in identifying the variety of DSDs in different precipitation systems, and it is a good indicator of rainfall overestimation or underestimation with the $R (Z_{H})$ relation (Aydin and Giridhar 1992; Brandes et al. 2004; Ryzhkov et al. 2005a; Gu et al. 2011; Matrosov et al. 2016). For a given $Z_{H}$, the large (small) values of $Z_{DR}$ indicate the DSDs with bigger (smaller) mean raindrop size. In this study, the microphysical features of different rain regimes are compared with the $Z_{DR}$ versus $Z_{H}$ pair, while the performances of QPE with different rainfall estimators in $Z_{DR}$-$Z_{DR}$ space are quantitatively analyzed.

Each polarimetric radar–based rainfall estimator has its own problems under different conditions. For example, $R (Z_{H})$ and $R (Z_{H}, Z_{DR})$ are sensitive to radar attenuation in heavy rain, while $R (K_{DP})$ is noisy in light precipitation (Ryzhkov et al. 2005a). This means that a composite algorithm is needed for obtaining more accurate QPE results (Cifelli et al. 2002; Silvestro et al. 2009; Bringi et al. 2011). The composite algorithm $R (C)$ is mainly based on the $R (Z_{H})$-estimated rain rate and the value of $Z_{DR}$. Generally, $R (K_{DP})$ is used in heavy precipitation and $R (Z_{H})$ is used in light rain, while $R (Z_{H}, Z_{DR})$ is used in light rain with high values of $Z_{DR}$. However, the thresholds of $Z_{H}$, $Z_{DR}$, and $K_{DP}$ in composite algorithms vary with different climate systems, and the relationship of $Z_{H}$ and $Z_{DR}$ has yet to be addressed in eastern China. A new composite algorithm is proposed based on the quantitative analysis of QPE performances with different rainfall estimators in $Z_{H}$-$Z_{DR}$ distribution space and has proven to be better than each single estimator in the study.

A description of data and analysis methods is presented in section 2. QPE performances of $R (Z_{H})$, $R (Z_{H}, Z_{DR})$, and $R (K_{DP})$ are evaluated in section 3. Dependence on rain microphysics is discussed in section 4. A summary of results is provided in the concluding section.

## 2. Data and methods

### a. NJU-CPOL radar

The radar data used in the study are from NJU-CPOL deployed at the Changfeng station in Anhui Province during OPACC from 1 June to 31 July 2014 (Fig. 1). The data possess a 1.2° beamwidth and a 75-m radial resolution. A modified volume coverage pattern 11 mode (VCP11) was operated during the OPACC. The modified VCP11 is similar to that used in the Weather Surveillance Radar-1988 Doppler (WSR-88D) in the United States, which consists of 14-elevation plan position indicator (PRI) scans between 0.5° and 19.5° (Crum et al. 1993) and takes about 7 min to complete. NJU-CPOL adds a 90° elevation vertical pointing scan at the end of each VCP11 for $Z_{DR}$ calibration purposes. NJU-CPOL also performs range–height indicator (RHI) scans to probe the vertical structure of rainfall systems as needed. In this paper we use 1.5° elevation angle PRI data within 100 km of NJU-CPOL to estimate surface rainfall.

The good quality of NJU-CPOL data is a priori to obtaining accurate radar QPE. NJU-CPOL data quality control (QC) procedures used in this study are similar to those in Huang et al. (2016), which can be summarized as follows:

1) Estimator $Z_{H}$ is well calibrated through a metal sphere experiment (Scarchilli et al. 1995). The system biases of $Z_{DR}$ are calibrated using vertically pointing data where $Z_{DR}$ should be approximately zero in light rain. We specifically chose data from all vertically pointing data below the melting layer in light rain to calculate the $Z_{DR}$ biases for $Z_{DR}$ calibration in every IOP. The $Z_{DR}$ biases vary between 0.3 and 0.5 dB throughout the OPACC.

2) Nonmeteorological echoes, including ground clutter, biological scatterers, and anomalous propagation, are eliminated when $\rho_{hi}$ is below 0.85.

3) To accurately estimate $K_{DP}$, we process the phase data in two steps: (i) the system differential phase (i.e., $\phi_{DP}$) is corrected with the vertically pointing scan data to ensure the $\phi_{DP}$ value in the first gate is close to zero, and (ii) after unfolding, $\phi_{DP}$ smoothing and $K_{DP}$ are calculated using the enhanced linear programming method from Huang et al. (2016). Because of the nonnegative

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**Table 1. Rainfall cases and their associated weather systems.**

<table>
<thead>
<tr>
<th>Case</th>
<th>Period</th>
<th>Total time (h)</th>
<th>Weather system</th>
</tr>
</thead>
<tbody>
<tr>
<td>IOP1</td>
<td>From 31 May to 1 Jun 2014</td>
<td>17</td>
<td>Squall line</td>
</tr>
<tr>
<td>IOP3</td>
<td>14–15 Jun 2014</td>
<td>24</td>
<td>Mei-yu rainband</td>
</tr>
<tr>
<td>IOP5</td>
<td>25–26 Jun 2014</td>
<td>12</td>
<td>Mei-yu rainband</td>
</tr>
<tr>
<td>IOP6</td>
<td>From 30 Jun to 1 Jul 2014</td>
<td>14</td>
<td>Mei-yu rainband</td>
</tr>
<tr>
<td>IOP7</td>
<td>4 Jul 2014</td>
<td>9</td>
<td>Mei-yu rainband</td>
</tr>
<tr>
<td>IOP8</td>
<td>11–12 Jul 2014</td>
<td>16</td>
<td>Mei-yu rainband</td>
</tr>
<tr>
<td>IOP10</td>
<td>24 Jul 2014</td>
<td>8</td>
<td>Typhoon rainband</td>
</tr>
<tr>
<td>IOP11</td>
<td>30 Jul 2014</td>
<td>7</td>
<td>Squall line</td>
</tr>
</tbody>
</table>

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constraint used, the estimated $K_{DP}$ values from linear programming method will never be negative, even at the light rain region or the leeside of the “bump” region.

4) The measured $Z_H$ and $Z_{DR}$ are corrected for rain attenuation using $\phi_{DP}$ (Bringi et al. 2011), which assumes that the specific horizontal attenuation $A_H$ (dB km$^{-1}$) and specific differential attenuation $A_{DP}$ (dB km$^{-1}$) are almost linearly proportional to specific differential phase (i.e., $K_{DP}$). Based on the 2DVD observations, the relations of $A_H = 0.085K_{DP}$ and $A_{DP} = 0.02K_{DP}$ are derived and used in this study.

5) Median filter and running mean over five gates in radial direction are used for $Z_H$ and $Z_{DR}$ to remove outliers and reduce random fluctuation.

b. DSD measurements

A 2DVD located in Nanjing at a distance of 171 km from NJU-CPOL (Fig. 1) is used to measure DSDs for deriving synthetic polarimetric radar parameters and radar-based QPEs. This setup is not ideal but is acceptable to obtain representative DSDs since the 2DVD and NJU-CPOL are both located in the same climate environment in the Yangtze–Huaibei River basin in eastern China. This newly designed third-generation 2DVD is equipped with faster cameras. To reduce splash effects, only the drops in the inner part of the measurement inlet are counted. Its vertical and horizontal resolutions for raindrop diameter are better than 0.19 mm.

Two years of 2DVD data during the summer seasons of 2014 and 2015 are used in this study. The 1-min-averaged data with total number of drops less than 50 and rain rate less than 0.1 mm h$^{-1}$ are considered as noise and are discarded (Islam 2014; You et al. 2014a). A total of 22,896 one-minute-averaged DSD samples are available for analysis in this study. Synthetic radar variables are calculated from 2DVD observations using the T matrix scattering approach for nonspherical particles (Zhang et al. 2001). The axis ratio of raindrops in calculating backscattering amplitudes used in this study is based on Brandes et al. (2002). Since the effects of temperature on synthetic radar variables are negligibly small (Aydin and Giridhar 1992), the raindrop temperature is assumed to be 10°C and the canting angle is set to 0°.

The equivalent radar reflectivity factor $Z_{hv}$ (mm$^6$ m$^{-3}$) is defined by

$$Z_{hv} = \frac{4\pi^4}{\pi^4} |K_w|^2 \int_{D_{\text{min}}}^{D_{\text{max}}} |f_{hv,vv}(\pi, D)|^2 N(D) dD,$$  

where $D$ (mm) is the equivalent diameter and $N(D)$ (m$^{-3}$ mm$^{-1}$) is the number concentration of raindrops in a unit volume of air and in the unit size interval; $\lambda$ is the radar wavelength (mm); $D_{\text{min}}$ and $D_{\text{max}}$ are the minimum and maximum drop diameter of the actual DSD, respectively; $K_w$ is the dielectric constant factor of water; and $f_{hv,vv}(\pi, D)$ (mm) is the backscattering amplitude at the horizontal or vertical polarization. The horizontal equivalent reflectivity factor (i.e., $Z_H$) represented in decibels is $Z_H = 10\log_{10}Z_{hv}^{10}$ (dBZ).

The linear and log forms of differential reflectivity (i.e., $Z_{dr}$ and $Z_{DR}$; dB) are defined as follows:

$$Z_{DR} = 10\log_{10}Z_{hv}^{10} = 10\log_{10}Z_{dr}^{10},$$  

where $Z_v$ is the vertical equivalent reflectivity factor.

The specific differential phase (i.e., $K_{DP}$; ° km$^{-1}$) is obtained in terms of the forward-scattering amplitude $f(0, D)$ (mm) as follows:

$$K_{DP} = 10^{-3} \frac{180}{\pi} \text{Re} \left\{ \int_{D_{\text{min}}}^{D_{\text{max}}} \left[ f_{hv}(0, D) - f_{vv}(0, D) \right] N(D) dD \right\},$$  

where Re refers to the real part of the integral, and $f_{hv}(0, D)$ and $f_{vv}(0, D)$ (mm) are the forward-scattering amplitudes at the horizontal and vertical polarizations, respectively.

For QPE, three rainfall estimators are derived from the 2DVD dataset in the summers of 2014 and 2015. The best-fit equation of $R(Z_h)$ used here is the same as Wen et al. (2016). The relationship is $Z_h = 232R^{1.34}$, which is close to the recommendation by the National Weather Service (NWS) for the WSR-88D precipitation-processing subsystem (Rosenfeld et al. 1993) for tropical systems ($Z_h = 230R^{1.25}$). When inverted, the disdrometer-based $R(Z_h)$ relationship is

$$R(Z_h) = 0.0171Z_h^{0.746}.$$  

For the $R(Z_h, Z_{dr})$ relationship, the equation is fitted as

$$R(Z_h, Z_{dr}) = 0.0085Z_h^{0.896}Z_{dr}^{-2.877}.$$  

The coefficients $a$ and $b$ for a C-band radar’s $R(K_{DP}) = aK_{DP}^b$ relationship have been computed in previous studies (Table 2) either from simulated DSDs (Scarchilli et al. 1993) or measured DSDs during baiu.

<table>
<thead>
<tr>
<th>Origin</th>
<th>$R(K_{DP})$</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>East China</td>
<td>$R = 31.1K_{DP}^{0.77}$</td>
<td>—</td>
</tr>
<tr>
<td>Okinawa</td>
<td>$R = 28.8K_{DP}^{0.55}$</td>
<td>Bringi et al. (2006)</td>
</tr>
<tr>
<td>Darwin</td>
<td>$R = 34.6K_{DP}^{0.51}$</td>
<td>Keenan et al. (1994)</td>
</tr>
<tr>
<td>Taiwan</td>
<td>$R = 35.4K_{DP}^{0.50}$</td>
<td>Wang et al. (2013)</td>
</tr>
<tr>
<td>Oklahoma</td>
<td>$R = 25.3K_{DP}^{0.78}$</td>
<td>Gu et al. (2011)</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>$R = 24.7K_{DP}^{0.81}$</td>
<td>Bringi et al. (2011)</td>
</tr>
<tr>
<td>Simulation</td>
<td>$R = 19.8K_{DP}^{0.71}$</td>
<td>Scarchilli et al. (1993)</td>
</tr>
</tbody>
</table>
frontrains (Bringi et al. 2006), typhoons (Wang et al. 2013),
thunderstorms (Keenan et al. 1994), or continental precipitations (Bringi et al. 2011; Gu et al. 2011). The best-fit equation of \( R(K_{DP}) \) derived from the 2DVD data in the summertime in eastern China is

\[
R(K_{DP}) = 31.1 K_{DP}^{0.77}.
\]  

Note that the relationship of \( R(K_{DP}) \) obtained for the data in eastern China is different from the relationships derived for data in other regions. Overall, our relationship is close to the one derived by Bringi et al. (2006) from Okinawa, Japan, in a baiu front. However, the coefficient \( a \) for eastern China is higher than that for continental precipitation but lower than that for typhoons and thunderstorms. This means that for a given \( K_{DP} \), 1° km\(^{-1} \), for example, estimated rainfall is almost 20% higher than the value using the continental relation and 15% lower than the value using the typhoon relation. Notice that the multiplicative coefficient \( a \) can be sensitive to local climatology (Bringi et al. 2003); therefore, the \( R(Z_h) \), \( R(Z_h, Z_{dr}) \), and \( R(K_{DP}) \) estimators derived from 2DVD data in eastern China can represent the unique DSD characteristics in that specific area and allow more accurate QPEs.

Figures 2a–c show the scatterplots of three rainfall estimators \((4), (5), \) and \((6)\) versus the rain rate calculated from the 2DVD data, which demonstrate the performances of the algorithms under the “ideal conditions.” It can be seen that \( R(Z_h) \) performs the worst with large scatter and many extreme overestimations, while \( R(Z_h, Z_{dr}) \) and \( R(K_{DP}) \) are much better, and the consistency of \( R(Z_h, Z_{dr}) \) is the best of the three estimators under ideal conditions. The result is similar to that in Bringi et al. (2011).

c. Comparison with rain gauges

Gauge observations are widely accepted as the ground truth and are used to evaluate the performance of radar-based QPE algorithms. The tipping-bucket gauges used in this study provide 1-h rain accumulation data. A total of 352 rain gauges located within 5–100 km from NJU-CPOL are included in the analysis (Fig. 1).

To quantify the performance of each QPE algorithm, the normalized absolute error (NE), root-mean-square error (RMSE), and correlation coefficient (CC) are calculated:

\[
NE = \frac{\left( \frac{1}{N} \sum_{i=1}^{N} (R_{R,i} - R_{G,i}) \right)}{R_{G}},
\]  

\[
RMSE = \left[ \frac{1}{N} \sum_{i=1}^{N} (R_{R,i} - R_{G,i})^2 \right]^{1/2}, \quad \text{and}
\]  

\[
CC = \frac{\sum_{i=1}^{N} \left( R_{R,i} - \overline{R}_R \right) \left( R_{G,i} - \overline{R}_G \right)}{\left[ \sum_{i=1}^{N} \left( R_{R,i} - \overline{R}_R \right)^2 \right]^{1/2} \left[ \sum_{i=1}^{N} \left( R_{G,i} - \overline{R}_G \right)^2 \right]^{1/2}}.
\]

Here \( N \) is the number of \( R_{R} \) and \( R_{G} \) pairs, and \( \overline{R}_R \) and \( \overline{R}_G \) are the averaged rain accumulation for the radar estimates and gauge measurements, respectively. The polarimetric radar–based QPE at each rain gauge is computed by averaging radar variables over the area of 1 km (range) \( \times 1° \) (azimuth) centered on each rain gauge.
3. Polarimetric radar–based QPE results

a. Statistical performance of three polarimetric radar–based QPE schemes

To evaluate the statistical performance of the three rainfall estimators, the OPACC NJU-CPOL data (listed in Table 1) are used to estimate hourly rainfall at each rain gauge. Plots of the number density function (NDF) between the estimated and gauge-observed hourly rainfall (Fig. 3) show that the traditional estimator $R(Z_h)$ performs the worst, with the largest data scatter among all three estimators. The CC, RMSE, and NE of $R(Z_h)$ are 0.76, 5.32 mm, and 0.59, respectively (Fig. 3a). The two polarimetric estimators $R(Z_h, Z_{dr})$ and $R(K_{DP})$ obviously improve the rainfall estimations, benefitting from the use of polarimetric variables (Figs. 3b,c). Rainfall estimated from $R(Z_h, Z_{dr})$ is better than that from $R(Z_h)$, while the $K_{DP}$-based estimator $R(K_{DP})$ (Fig. 3c) provides the best agreement to the rain gauge observations. The CC (RMSE and NE) of $R(K_{DP})$ can reach as high (low) as 0.82 (3.35 mm and 0.44). In particular, the $K_{DP}$-based rainfall estimator has a much smaller deviation from rain gauge observations at moderate to heavy rain ($R > 10\, \text{mm h}^{-1}$), compared to the other two estimators. The performance of $R(K_{DP})$ is different from the results in ideal conditions (Fig. 2), but consistent with the previous studies (Brandes et al. 2001; Ryzhkov et al. 2005a; Bringi et al. 2011; Zhang 2016), which can be attributed to its advantage of being immune to the radar absolute calibration and attenuation and exhibiting lower variability to the DSD variations (compared to traditional $Z_h$–$R$ relations). It is also noted that $R(K_{DP})$ has a large bias in light rain ($R < 1\, \text{mm h}^{-1}$) due to the noisy $K_{DP}$.

b. QPE performances in different convective systems

Previous studies have shown that radar QPE performances change easily across different precipitation systems (Ryzhkov et al. 2005a; Wang et al. 2013; You et al. 2014b; Matrosov et al. 2016). To examine the QPE performance in different precipitation systems in eastern China in the summertime, three cases (mei-yu rainband, typhoon rainband, and squall line) with heavy precipitation are selected for further study, as shown in Table 3. Case 1 (IOP8) is a typical mei-yu rainband. The mei-yu rainband is the main precipitation system during the period from mid-June to mid-July in the Yangtze–Huaihe River basin in eastern China. This type of rainfall system can last from several hours to several days, bringing precipitation over a large area, and can sometimes produce torrential rainfall and cause extreme flooding. Case 2 (IOP10) is a rainfall system consisting of several outer rainbands of Typhoon Matmo (2014). One of the rainbands had passed through the observation area and was observed by NJU-CPOL. This kind of landfalling typhoon could hit the observation area in eastern China every year and potentially cause enormous damage with extremely heavy rainfall. Case 3 (IOP11) is a squall line that occurred in late July 2014. The system initiated in the observation area and moved from west to east. Squall line is one of the summertime extreme
TABLE 3. The QPE comparison results of CC, RMSE, and NE in the three cases.

<table>
<thead>
<tr>
<th>Estimator</th>
<th>CC</th>
<th>RMSE (mm)</th>
<th>NE</th>
</tr>
</thead>
<tbody>
<tr>
<td>IOP8 (mei-yu band)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R(Z_h)$</td>
<td>0.89</td>
<td>27.31</td>
<td>0.54</td>
</tr>
<tr>
<td>$R(Z_h, Z_{dr})$</td>
<td>0.87</td>
<td>22.48</td>
<td>0.43</td>
</tr>
<tr>
<td>$R(K_{DP})$</td>
<td>0.91</td>
<td>11.78</td>
<td>0.22</td>
</tr>
<tr>
<td>IOP10 (typhoon band)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R(Z_h)$</td>
<td>0.89</td>
<td>16.34</td>
<td>0.30</td>
</tr>
<tr>
<td>$R(Z_h, Z_{dr})$</td>
<td>0.90</td>
<td>14.21</td>
<td>0.25</td>
</tr>
<tr>
<td>$R(K_{DP})$</td>
<td>0.91</td>
<td>13.70</td>
<td>0.24</td>
</tr>
<tr>
<td>IOP11 (squall line)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R(Z_h)$</td>
<td>0.73</td>
<td>29.23</td>
<td>1.05</td>
</tr>
<tr>
<td>$R(Z_h, Z_{dr})$</td>
<td>0.82</td>
<td>17.79</td>
<td>0.63</td>
</tr>
<tr>
<td>$R(K_{DP})$</td>
<td>0.86</td>
<td>12.11</td>
<td>0.48</td>
</tr>
</tbody>
</table>

weather systems in eastern China. The short bursts of strong rainfall during severe convection can cause severe urban waterlogging disasters. Therefore, obtaining accurate QPEs for flood monitoring in these extreme precipitation systems is critically important during the summer season in eastern China.

Figures 4a–c show $Z_H$, $Z_{DR}$, and $K_{DP}$ of 1.5° elevation PPI scan of the mei-yu rainbow case (IOP8). Notice that there are several convection centers embedded in large-scale stratiform precipitation region. Values of $Z_H$ can exceed 55 dBZ, while $Z_{DR}$ is over 3 dB and $K_{DP}$ reaches 7° km$^{-1}$ in convection centers, which indicate that the instant rain rate at that location can be over 140 mm h$^{-1}$ [estimated using our rainfall estimator of $R(K_{DP})$ in (6)]. On the other hand, the precipitation in the stratiform regions is weak and has uniform spatial distribution, with $Z_H$ less than 40 dBZ while $Z_{DR}$ is less than 1.5 dB and $K_{DP}$ is less than 0.5° km$^{-1}$. PPI scans of the typhoon rainbow (IOP10) are shown in Figs. 4d–f. It can be seen in the areas of high reflectivity (40 < $Z_H$ < 55 dBZ) that $Z_{DR}$ is mainly lower than 3 dB. Since $Z_{DR}$ is a good measure of the median drop diameter, it indicates that the typhoon case is composed of small raindrops. Figures 4g–i show the value of $Z_H$, $Z_{DR}$, and $K_{DP}$ for the squall line (IOP11). The $Z_H$ in the leading convective region exceeds 60 dBZ, with $Z_{DR}$ over 3 dB and $K_{DP}$ over 7° km$^{-1}$. On the other hand, $Z_H$ is typically below 40 dBZ, with $Z_{DR}$ less than 1.5 dB and $K_{DP}$ below 0.5° km$^{-1}$ in the trailing stratiform region. The structure of strong convection in the leading edge accompanied by an extensive trailing stratiform region is the typical characteristic of a squall line (Park et al. 2009). The RHI scans show that the 20-dBZ radar echoes in the convective region of the squall line can reach 14 km, much higher than those of the mei-yu and typhoon (about 10 km, not shown). This indicates the squall line has a more distinct ice-phase process with a larger size particle due to the strong updraft, since the height of 20 dBZ is usually an indicator of how high the updraft can loft precipitation-size ice particles (Liu and Zipser 2005). In the stratiform region, the squall line and mei-yu exhibit a stronger brightband signature than typhoon between 4.5 and 5 km, with their maximum reflectivity of about 45 dBZ.

NJU-CPOL-derived rain accumulations using $R(Z_h)$, $R(Z_h, Z_{dr})$, and $R(K_{DP})$ are performed for the three cases and then compared with the rain gauge observations. The bias ratio bubble charts and scatterplots are presented in Figs. 5–7. Figure 5 shows the characteristics of the three polarimetric radar–based quantitative precipitation estimators for a 16-h period from 1600 UTC 11 July to 0800 UTC 12 July 2014 during the mei-yu rainbow (IOP8). A long-lasting precipitation episode was produced in this case with a maximum accumulated gauge observation of 138 mm in 16 h. The spatial distribution of the radar QPE bias ratio ($-R_G/R_C$) for radar–gauge pairs is illustrated in Figs. 5a, 5c, and 5e for the three QPE algorithms. Note that a bias ratio greater (less) than 1.0 indicates that radar overestimates (underestimates) the 16-h rainfall accumulation, while the values close to 1 represent excellent QPE performance. Apparently, $R(Z_h)$ shows overestimation of rainfall in almost all areas; over 80% of gauges have a bias ratio over 1.25. On the other hand, the overestimation of $R(Z_h, Z_{dr})$ is lessened, especially on the west side of NJU-CPOL in high precipitation accumulation region, where a certain proportion of gauge points are with bias ratios from 0.9 to 1.1. The result of $R(K_{DP})$ is the best in this mei-yu rainbow case, demonstrated by nearly a quarter of gauges with QPE bias within 10%.

With regard to the scatterplots of radar QPEs versus gauge observation in Figs. 5b, 5d, and 5f, the $R(Z_h)$ quantitative precipitation estimator shows a strong overestimation of rain with a normalized error of 0.54 and an RMSE of 27.31 mm. The performance of $R(Z_h, Z_{dr})$ is much better, with decreases in NE to 0.43 and in RMSE to 22.48 mm, indicating that the overestimation has been somewhat mitigated. Compared to the former two, $R(K_{DP})$ performs the best in the mei-yu rainbow with an NE of 0.22 and an RMSE of 11.78 mm.

The results of QPE for $R(Z_h)$, $R(Z_h, Z_{dr})$, and $R(K_{DP})$ methods in the typhoon rainbow (IOP10) are shown in Fig. 6. The $R(K_{DP})$ performs best, with an NE of 0.24 and an RMSE of 13.7 mm in general. The result of $R(Z_h)$ is not as good as that of $R(K_{DP})$; with an NE of 0.3 and an RMSE of 16.34 mm, nearly 70% of gauges are overestimated of rainfall. The overestimation in $R(Z_h, Z_{dr})$ is reduced slightly compared to $R(Z_h)$, with an NE of 0.25 and an RMSE of 14.21 mm.

The results of the QPEs in the squall line (IOP11) are shown in Fig. 7. As illustrated in previous studies, a large number of big drops or melting hail and graupel could exist in the leading edge of squall lines (Park et al. 2009),
which contribute to the high value of $Z_H$ in this kind of rainfall system, and $R(Z_h)$ would overestimate the rainfall (Giangrande and Ryzhkov 2008; Ryzhkov et al. 2013). The significant overestimation of rainfall using $R(Z_h)$ (Figs. 7a,b) is consistent with previous works, with the value of NE exceeding 1 and an RMSE of 29.23 mm. The result of $R(K_{DP})$ is the best among the three methods in this precipitation system. Compared to $R(Z_h)$ and $R(Z_H, Z_{dr})$, $R(K_{DP})$ yields results that are much closer to the gauge results: NE drops to 0.48 and RMSE decreases to 12.11 mm.

All the CC, RMSE, and NE scores of the three cases are listed in Table 3. Overall, $R(K_{DP})$ produces the best rain accumulation estimation for all the three cases, while $R(Z_h)$ performs the worst compared with the rain gauge observations. The three rainfall estimators perform differently in different convection systems. It is also noted that there is an obvious and persistent...
FIG. 5. Comparison of NJU-CPOL QPEs obtained using $R(Z_h)$, $R(Z_h, Z_{dr})$, and $R(K_{DP})$ with gauge observations using 16-h data in the mei-yu rainband. (a),(c),(e) Bubble charts show bias ratios ($5R_R/R_G$) between the QPEs and independent gauge observations, where the size of the circles represents the gauge-observed rainfall amount and the colors show the bias ratios. (b),(d),(f) Scatterplots show distribution of the 16-h QPEs vs the gauge observations.
FIG. 6. As in Fig. 5, but for gauge observations using 8-h data in the typhoon rainband case.
FIG. 7. As in Fig. 5, but for gauge observations using 8-h data in the squall-line case.
underestimation of heaviest rainfall (>75 mm) with a single $R(K_{DP})$ relation in mei-yu (Fig. 5) and particularly in the typhoon case (Fig. 6). Wang et al. (2013) compared $R$ and $K_{DP}$ relations measured in typhoon with those in thunderstorm, mei-yu, and continental precipitation and found that for a given $K_{DP}$, the estimated $R$ using the typhoon relationship is largest. This suggests that the underestimation of total rainfall with $R(K_{DP})$ in this study can be attributed to the use of a mean $R$ and $K_{DP}$ relation for summer rainfall instead of specific relations for typhoon or mei-yu. To improve the QPE of $R(K_{DP})$, an intercept adjustment for the $R$ and $K_{DP}$ relationship depending on the rain type is needed in the future.

4. Analysis of rain microphysics dependence

a. The relationship between synthetic radar variables derived from 2DVD

The scatterplot of $Z_{DR}$ versus $Z_H$ using 2DVD data in the summers of 2014 and 2015 (gray squares) is shown in Fig. 8, illustrating extreme $Z_{DR}$ variability for $Z_H > 45$ dBZ. The $Z_{DR}$ varies from 1 to 6 dB for $45 < Z_H < 55$ dBZ, and high values of $Z_{DR}$ can be associated with relatively moderate values of $Z_H$ when $30 < Z_H < 40$ dBZ. Overall, the best linear fit of $Z_{DR}$ versus $Z_H$ for $25 < Z_H < 45$ dBZ (gray line) for the entire 2DVD dataset is

$$Z_{DR} = 0.039Z_H - 0.64 \quad (25 < Z_H < 45 \text{ dBZ}),$$

which represents the statistical relationship of $Z_H$ and $Z_{DR}$ in the summer for eastern China. The green, red, and blue lines and scatterplots in Fig. 8 represent the distributions of $Z_{DR}$ versus $Z_H$ pairs in the mei-yu, typhoon, and squall-line cases that pass over the 2DVD site and the linear fits of the $Z_{DR}$ versus $Z_H$ for $25 < Z_H < 45$ dBZ, respectively. It can be seen that for a given $Z_H$, the mean value of $Z_{DR}$ is the largest in the squall-line case, the smallest in the typhoon case, and somewhere in the middle in the mei-yu rainband. The high $Z_{DR}$ region only consists of blue plus signs, indicating that this cluster of higher $Z_{DR}$ points in the 2DVD data is primarily associated with squall-line-type convection. The points of the typhoon case are mainly located in the low $Z_{DR}$ region. These results indicate that the variability of the relationship of the $Z_{DR}$ versus $Z_H$ pairs reflects the diversity of microphysical features in different precipitation systems.

b. Microphysical variability of different rainfall systems

The three normalized density distributions of $Z_{DR}$ versus $Z_H$ from the NJU-CPOL are compared in Figs. 9a–c. Only the data points with precipitation with $Z_H > 15$ dBZ are used for the analysis. The filled colors represent the normalized density of data from 5% to the highest occurrence frequency of 100%, and the black line represents the threshold of data normalized density of 1% to show the influence of extreme samples with low occurrence frequency.

A relatively low $Z_{DR}$ is noted for $Z_H > 40$ dBZ when the normalized density is over 5% in the mei-yu rainband case, consistent with the 2DVD observations in Fig. 8, indicating that the median drop diameter does not increase with increased $Z_H$; instead, the increased $Z_H$ is due to an increase in drop concentration. Similar median drop diameter characteristics in $Z_H$–$Z_{DR}$ space have been also found in a tropical precipitation event by Bringi et al. (2012). For the typhoon rainband case, $Z_{DR}$ is less than 1.2 dB when the normalized density is over 20%, which indicates that the typhoon rainband is dominated by small raindrops, also documented by Wang et al. (2016). However, when considering the low occurrence samples with the normalized density over 1%, the value of $Z_{DR}$ can exceed 2.5 dB when $Z_H > 45$ dBZ; it is similar to the characteristics of squall line and shows that low concentration of big raindrops can also exist in the typhoon rainband. Finally, the value of $Z_H$ is over 53 dBZ and $Z_{DR}$ reaches 2.2 dB in the squall-line case when the normalized density is over 5%, and $Z_{DR}$ exceeds 4 dB when the normalized density is over 1%, which confirms that the squall line contains bigger raindrops than the mei-yu rainband and typhoon rainband. As for the high-frequency center of the normalized density, which is filled with yellow color, mean $Z_H$ is 32 dBZ and $Z_{DR}$ is...
0.7 dB in the squall line. The values become 33 dBZ and 0.5 dB in the typhoon rainband and 32 dBZ and 0.5 dB in the mei-yu rainband, which also suggests that the squall line is composed of larger raindrops.

Figure 9d shows the mean values of $Z_{DR}$ along with $Z_H$ in the three cases, and the black line represents the mean values of $Z_{DR}$ along with $Z_H$ as measured by 2DVD in Fig. 8. For the same value of $Z_H$ (32 < $Z_H$ < 43 dBZ), the mean values of $Z_{DR}$ from the highest to the lowest are squall line, mei-yu rainband, and typhoon rainband, indicating that the mean drop size in the squall line is larger than that in the mei-yu rainband and typhoon rainband. The NJU-CPOL results are consistent with those of the 2DVD in Fig. 8.

c. QPE performance in $Z_H$–$Z_{DR}$ space

The above results reveal that the accuracy of radar QPEs varies in the three rainfall cases, while there also remains certain differences of microphysical features in these different rainfall systems. Therefore, it would be worthwhile to analyze the QPE performances in different $Z_H$–$Z_{DR}$ spaces, which represent different microphysical scenarios.

Figure 10 represents the mean NE of hourly quantitative precipitation estimators compared with gauge measurements in $Z_H$–$Z_{DR}$ space of the three analyzed precipitation cases. The spatial scale for averaging is 1 km (range) $\times$ 1° (azimuth) and the temporal scale for averaging is 1 h. Only the data points in all the three cases with hourly rain rate over 1 mm h$^{-1}$ are selected. The bin size of $Z_H$ and $Z_{DR}$ are 2 dBZ and 0.2 dB in the analysis, while QPE NEs are averaged and represented by filled color squares for each $Z_H$–$Z_{DR}$ bin. Figures 10a–c show the performance of the QPE algorithms $R(Z_b)$, $R(Z_{HP}, Z_{uk})$, and $R(K_{DP})$ in $Z_H$–$Z_{DR}$ space, respectively. The values of NE of $R(Z_b)$ are lower than the other two estimators in the area of 20 < $Z_H$ < 28 dBZ; however, the values of NE increase rapidly along with the increase of $Z_H$ and $Z_{DR}$.
and go up to 1.2 when $30 < Z_H < 40 \text{ dBZ}$. When $Z_H > 40 \text{ dBZ}$ and $Z_{DR} > 1.2 \text{ dB}$, the NE of $R(Z_h)$ exceeds 1.2 and goes up to 3. The fluctuation of QPE performance with $R(Z_h)$ in different $Z_H$–$Z_{DR}$ bins reflects that $R(Z_h)$ is easily affected by the variability of rainfall DSDs, especially the large value of $Z_H$.

On the other hand, the NEs of $R(Z_h, Z_{dr})$ and $R(K_{DP})$ do not present this kind of variability in general. The NE of $R(Z_h, Z_{dr})$ performs best when $28 < Z_H < 40 \text{ dBZ}$ and the values of $Z_{DR}$ are above the black slanted line as represented in Fig. 10b, with the values mainly less than 0.8 in this region. The NEs of $R(Z_h, Z_{dr})$ in the region of $Z_H > 40 \text{ dBZ}$ and $Z_{DR} > 1.2 \text{ dB}$ are better than those of $R(Z_h)$, but their accuracy is still unsatisfactory. The NEs of $R(K_{DP})$ perform best on the right side of the black slash where $Z_H > 28 \text{ dBZ}$, as shown in Fig. 10c. The NEs are lower than the other two estimators in this area of the $Z_H$–$Z_{DR}$ distribution, while NEs in most bins in Figs. 10a and 10b exceed 0.8 but are less than 0.6 in Fig. 10c. Overall, the performance of $R(K_{DP})$ is the best in the area of $Z_H > 40 \text{ dBZ}$ and $Z_{DR} > 1.2 \text{ dB}$ in extreme rainfall DSD situations.

d. A composite algorithm of QPE

The performances of the three rainfall estimators indicate that each algorithm has its own strength: 1) $R(Z_h)$ is easily affected by the variability of rainfall DSDs and is not suitable for heavy precipitation; 2) $R(Z_h, Z_{dr})$ can mitigate the effects of DSD variability while the accuracy of $Z_{DR}$ can be easily distorted by attenuation, partial beam blockage, and contamination from melting hail; and 3) $R(K_{DP})$ is advantageous in heavy rainfall but is noisy in light precipitation. Previous studies have shown that there are two possible ways to improve the radar QPE accuracy of a single estimator: 1) by establishing the particular rain-rate estimator from $Z_H$–$Z_{DR}$ space data for a specific rain type with a prevalent DSD (Matrosov et al. 2016) and 2) by constructing a composite estimator by combining strength among different rainfall estimators (Ryzhkov et al. 2005a). Owing to the significantly lower numbers of 2DVD sampling typhoon (2478 one-minute records) and squall line (1234 one-minute records) compared with mei-yu (11 923 one-minute records), we could only use the composite
estimator approach in this study. A new composite algorithm $R(C)$ that combined strength among different rainfall estimators is proposed. Thresholds of $R(C)$ used in this study are picked based on the minimum errors of three radar estimators in the $Z_H-Z_{DR}$ space as indicated by the black lines in Fig. 10. The following is a description of $R(C)$:

\begin{align}
R(C) &= R(Z_h) \quad \text{if } Z_H < 28 \text{ dBZ}, \\
R(C) &= R(Z_{h}, Z_{dr}) \quad \text{if } 28 < Z_H < 40 \text{ dBZ} \quad \text{and} \\
Z_{DR} &> (0.1 \times Z_H - 2.6) \text{ dB}; \quad \text{and} \\
R(C) &= R(K_{dp}) \quad \text{if } Z_H > 40 \text{ dBZ} \quad \text{or} \\
Z_{DR} &< (0.1 \times Z_H - 2.6) \text{ dB}
\end{align}

when $28 < Z_H < 40$ dBZ.

where estimators $R(Z_h)$, $R(Z_{h}, Z_{dr})$, and $R(K_{dp})$ are determined by (4), (5), and (6), respectively.

The performance of the composite algorithm $R(C)$ is shown in Fig. 10d. It can be seen that values of NEs for $R(C)$ are less than the three estimators in the whole $Z_H-Z_{DR}$ space. The advantages of each single rainfall estimator in certain $Z_H-Z_{DR}$ distribution areas are shown in Fig. 10, which proves that the composite algorithm is able to take advantage of the three rainfall estimators and produce the best QPE results. This composite algorithm was also run for all eight precipitation IOPs and again outperforms any single radar QPE estimator (not shown).

5. Summary

In this paper, polarimetric radar rain estimation is studied and improved by using NJU-CPOL and 2DVD data from the summers of 2014 and 2015 in the Yangtze–Huaire River basin in eastern China. Three rainfall estimators of $R(Z_h)$, $R(Z_{h}, Z_{dr})$, and $R(K_{dp})$ are derived using the 2DVD-measured DSDs in eastern China. Three rain cases in different kind of weather systems are used to evaluate the performance of the three quantitative precipitation estimators. The microphysical features of these rainfall systems are analyzed to show the variability of DSDs in different rain regimes and their effects on the accuracy of QPEs. The trade-offs among different rainfall estimators suggest the potential benefit of using a composite rainfall estimator. The main conclusions of this study can be summarized as follows:

1) To obtain accurate polarimetric radar QPE in severe weather systems in eastern China, the radar rainfall estimators of $R(Z_h)$, $R(Z_{h}, Z_{dr})$, and $R(K_{dp})$ are established from a 2DVD data and T matrix calculation for the data collected in the summers of 2014 and 2015. The coefficients in the rainfall estimators are somewhat different from those obtained by the similar studies from other regions. In addition, it is found that raindrops in the summer of eastern China are characterized small mean size and high number concentration.

2) Three rain cases in three different weather systems, which include a mei-yu rainband, a typhoon rainband, and a squall line, are analyzed and used for the QPE study. The cases represent the different types of severe weather systems that can produce heavy precipitation in the summer of eastern China every year. The rainfall accumulation of the three rainfall estimators are compared with rain gauges. The QPE scores of $R(Z_h)$ are lowest in the three heavy precipitation cases. The performances of $R(Z_h, Z_{dr})$ are improved because of the limited mitigation of DSD variability by using $Z_{DR}$. The result of $R(K_{dp})$ is superior to the other two methods, especially in heavy precipitation.

3) The microphysical features of different rain regimes are analyzed. The distributions of $Z_{DR}$ versus $Z_H$ are useful in identifying the variety of DSDs in different precipitation systems. The analysis shows that the mean size of raindrops in the squall line is the largest while the mei-yu rainband and typhoon rainband are mostly composed of smaller raindrops. The variability of DSDs from different rain regimes is consistent with QPE results, that is, the cases with larger raindrops have an overestimation of $R(Z_h)$. The hourly rainfall normalized errors of $R(Z_h)$, $R(Z_{h}, Z_{dr})$, $R(K_{dp})$, and the composite algorithm $R(C)$ in $Z_H-Z_{DR}$ space are analyzed. A composite rainfall algorithm with obtained thresholds from QPE results of the three rainfall estimators is proposed to improve the performance of QPE.

It is shown that the composite algorithm $R(C)$ is able to take advantage of the three rainfall estimators and produce the best QPE results. Compared with the previous composite method that subjectively determined the thresholds, this composite algorithm determines thresholds more objectively based on the QPE error distribution at a given $Z_H-Z_{DR}$ space. It is also intuitive to think that rain estimation can be further improved by using separate estimators for different types of rain. However, as there are not sufficient data samples to separately derive stable relations for typhoon and squall-line QPE, the mean estimators are used in this study. We will derive stable separate relations when a bigger dataset is available in the future.

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