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Radar-derived quantitative precipitation estimation in complex terrain over the eastern Tibetan Plateau

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ABSTRACT

Quantitative precipitation estimation (QPE) is one of the important applications of weather radars. However, in complex terrain such as Tibetan Plateau, it is a challenging task to obtain an optimal *Z–R* relation due to the complex spatial and temporal variability in precipitation microphysics. This paper develops two radar QPE schemes respectively based on Reflectivity Threshold (RT) and Storm Cell Identification and Tracking (SCIT) algorithms using observations from 11 Doppler weather radars and 3264 rain gauges over the Eastern Tibetan Plateau (ETP). These two QPE methodologies are evaluated extensively using four precipitation events that are characterized by different meteorological features. Precipitation characteristics of independent storm cells associated with these four events, as well as the storm-scale differences, are investigated using short-term vertical profile of reflectivity (VPR) clusters. Evaluation results show that the SCIT-based rainfall approach performs better than the simple RT-based method for all precipitation events in terms of score comparison using validation gauge measurements as references. It is also found that the SCIT-based approach can effectively mitigate the local error of radar QPE and represent the precipitation spatiotemporal variability better than the RT-based scheme.

1. Introduction

Radar quantitative precipitation estimation (QPE) is an active and vibrant field with numerous accomplishments resulting in practical applications such as worldwide deployment of weather radars and urban scale flood application of dense radar networks (e.g., Yoshikawa et al., 2012; Chen and Chandrasekar, 2015; Shimamura et al., 2016; Chandrasekar et al., 2018). However, fundamental challenges in radar QPE still exist from both physical science and radar engineering points of view (Cifelli and Chandrasekar, 2010). On the one hand, the performance of radar QPE greatly relies on the physical model of raindrop size distribution (DSD) and the relation of the physical model to radar parameters. The precipitation microphysics in different storms or different regimes within a single storm cell may vary due to the complex internal cloud microphysical processes and/or external environmental factors (Chapon et al., 2008; Lee and Zawadzki, 2005; Smith et al., 2009; Yoshikawa et al., 2014). As a result, the inherent errors associated with the radar reflectivity and rainfall rate relationships (i.e., *Z–R* relations) derived for such nonuniformly distributed precipitation are difficult to remove (Bringi and Chandrasekar, 2001; Steiner and Smith, 2000; Cifelli and Chandrasekar, 2010). On the other hand, the system engineering issues including radar measurement height, beam broadening, and coverage limitations also pose challenges to radar QPE (Fulton et al., 1998; Chen and Chandrasekar, 2015). Such engineering challenges are especially obvious in operational or urban environments (Chandrasekar et al., 2018; Cifelli et al., 2018). Both the physical and engineering considerations make it difficult to find an ideal *Z-R* relation that is able to capture the spatial and temporal variability of precipitation in different storm seasons for a certain region.

A large number of previous studies have been devoted to improving radar QPE using precipitation measurements from rain gauges. The regional precipitation climatology derived using long-term radar and

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gauge observations is a useful tool to guide the development of radar rainfall products (Crochet, 2009; Nesbitt et al., 2006). Rain gauge data are also commonly used to conduct radar QPE mean-field-bias correction (e.g., Seo et al., 1999) and local bias correction (e.g., Zhang et al., 2016; Willie et al., 2017). However, most of the previous research focused on single *Z-R* relation-based analysis, which is not enough since different rain types may coexist especially in large-scale precipitation systems such as typhoon and Meiyu Front in China (Gou et al., 2014). In recent years, different empirical *Z-R* relations are used for different surface precipitation types such as stratiform or convective rain. Typical examples include the multi-radar multi-sensor (MRMS) system developed by Zhang et al. (2016), which adopts different *Z-R* relations for warm/cool stratiform rain and convective rain and hail. In addition, dense radar-gauge pairs may supply very useful feedback information for the quantitative reconstruction of *Z-R* relationships (Alfieri et al., 2010).

In complex terrains such as Northern California (Willie et al., 2017; Cifelli et al., 2018) or Tibetan Plateau (TP), the selection of appropriate *Z-R* relation is more challenging due to additional environment factors such as partial beam blockage (PBB) and bright-band (BB) contamination (Kitchen et al., 1994; Fulton et al., 1998; Willie et al., 2016). The orographic enhancement in complex terrain also has significant impacts on regional rainfall climatology (White et al., 2003). In this paper, a network of 11 Doppler weather radars and a dense rain gauge network over the Eastern Tibetan Plateau (ETP) are used to demonstrate radar rainfall performance in this complex terrain typically influenced by its unique topography and climate. Two adaptive QPE schemes are developed to dynamically reconstruct radar rainfall relations by fitting real-time radar-gauge rainfall observations using probability matching method (PMM: Rosenfeld et al., 1994). One is based on reflectivity threshold (RT), which assumes that similar radar echoes are homogeneous and fitting of *Z–R* relationship is done at every 5 dBZ intervals. The other one is based on the SCIT algorithm (Johnson et al., 1998) that refines three-dimensional multi-radar mosaic grids into independent storm regions to capture storm-scale or regional precipitation features (Gou et al., 2015). The microphysical principles of these two QPE schemes, their representative capability in convective conditions induced by orographic enhancement, as well as their rainfall performance over such a complex terrain are detailed in this paper. In addition, the ground radar based storm-scale VPR is investigated to reveal the microphysical differences between storm cells.

The main goal of this study is to address the aforementioned issues regarding the SCIT-based approach based on four precipitation events over the ETP. Section 2 introduces the datasets and QPE methods. Section 3 details the precipitation events used for evaluation and their microphysical differences during the storm evolutions through investigating the storm-scale VPRs. The evaluation results of the RT and SCIT based QPE algorithms are presented in Section 4. Section 5 summarizes the main points of this paper and suggests directions for future research.

2. Data and methodology

2.1. Study area

The ETP is located near the Hengduan Mountains, Southwest of China. Fig. 1 illustrates the digital elevation map (DEM) of China and particularly for this study domain (102°E–111°E, 28°N–33°N). Fig. 1b shows that the region of interest in this study extends from Hengduan Mountains to Wushan Mountains to the east, Ta-pa Mountains to the north, Dalou Mountains to the southeast, and the Yunnan-Guizhou Plateau to the southwest. It covers over 260,000 km^2 in total with an average elevation surpassing 4000 m above mean sea level (MSL) in the west, 3000 m above MSL in the north, and 2000 m above MSL in the south. The ETP exerts a direct influence on the social and economic development in this region, due to its multiple climatic systems, complex geomorphology, and various internal and external geological and ecological impacts. The ETP is characterized by the unique interactions among the atmosphere, hydrosphere, and biosphere. In particular, special atmospheric and active hydrological processes occur frequently on multiple scales on the ETP. These processes form the fundamental basis of its unique geography and enable it to generate considerable impacts on regional precipitation microphysics.

2.2. Radar and gauge network

11 Doppler weather radars are currently deployed for severe weather warning and forecast operations in this region. The specific locations and basic system specifications of these 11 radars are listed in Table 1. The radar type is specified according to its operating frequency and different manufacturers. SA/SC in Table 1 both mean S-band, whereas CD means C-band. The radial resolutions of SC and CD radars are configured as 250 m with an azimuthal resolution of 1°. The SA radars are set with resolution of 1000 m by 0.98°. The radar volume scan modes are all configured as the standard volume coverage pattern with sweep elevations set at 0.5°, 1.5°, 2.4°, 3.5°, 4.9°, 5.6°, 6.5°, 7.9°, 9.5°, 14.5°, and 19.5°. Such precipitation mode is used for meteorological operations. It takes about 6 min to complete a volume scan, and the base-level (level II) data are archived as volume scan files. The maximum radar reflectivity radial ranges in Table 1 are determined by the configurations of pulse repetition frequency (PRF), where SC and CD radars use the same PRF while SA adopts different PRF at different scan elevations. The coverage map of each of these 11 radars and heights of the lowest radar reflectivity that can be used to derive QPE are depicted in Fig. 2a. The radar network topology in Fig. 2a also shows its potential capability to observe various weather phenomena passing through the ETP.

There are 3264 rain gauges over the ETP (see Fig. 2b), most of which are tipping-bucket gauges with one-minute temporal resolution for real-time measurement, enabling them to capture the evolution of fine-scale precipitation events. The gauge observations are uploaded and transferred to the meteorological bureau at the municipal, provincial and national levels in order and in near real-time. Such dense rain gauge network also ensures the capability of SCIT to capture and represent storm-scale or regional precipitation processes.

The RT and SCIT based radar QPE algorithms are described in Section 2.3. Before they are evaluated on an hourly basis, the hourly rainfall observations from rain gauges are quality-controlled via the procedure shown in Fig. 3: (1) the data series with interrupted transfer reports are removed to ensure the subsequent processing; (2) with the reflectivity aloft two empirical *Z–R* relationships (i.e., $Z = 640R^{1.6}$ and $Z = 200R^{1.6}$) are applied to estimate the possible maximum ($R_{\max}$) and minimum ($R_{\min}$) rain gauge hourly measurements, respectively. Those lying outside of [$R_{\min} - 5$, $R_{\max} + 5$] are removed from the raw dataset; (3) if the gauge observation is < 0.1 mm but corresponding radar estimation is > 5 mm, the gauge is assumed jammed likely due to tree leaves, insects, and/or evaporation. If the gauge observation is > 5 mm but corresponding radar estimation is < 0.1 mm, the bucket is suspected to have provided a false reading, and these observations are not used; (4) The remaining data are further checked using the ratio of rainfall estimation (for a given gauge location) using the nearest five surrounding gauges based on inverse distance weighting method (Lloyd, 2005), and the measured rainfall by the gauge at the same location. The gauge data point is abandoned in the subsequent cross-validation if the ratio is higher than four.

2.3. RT and SCIT-based Z–R relationship fitting

Before the implementation of *Z–R* relationships, radar base-level volume data is first quality-controlled to eliminate ground clutter using the fuzzy logic approach described in Berenguer et al. (2006). Then, the radar data at polar coordinates are mapped onto Cartesian grids with a

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