



Dynamic rainfall mapping using multi-radar multi-gauge observations in changing synoptic environments

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Overview

It is well known that the performance of radar-derived quantitative precipitation estimates greatly relies on the physical model of the raindrop size distribution (DSD) and the relation between the physical model and radar parameters. However, incorporating changing precipitation microphysics to dynamically adjust the radar reflectivity (Z) and rain rate (R) relations can be challenging for real-time applications. In this paper, two adaptive radar rainfall approaches are developed based on the radar-gauge feedback mechanism using 16 S-band Doppler weather radars and 4579 surface rain gauges deployed over the Eastern JiangHuai River Basin (EJRB) in China. Although the Z - R relations in both approaches are dynamically adjusted within a single precipitation system, one is using a single global optimal (SGO) Z - R relation, whereas the other is using different Z - R relations for different storm cells identified by a storm cell identification and tracking (SCIT) algorithm. Four precipitation events featured by different rainfall microphysical characteristics are investigated to demonstrate the performances of these two rainfall mapping methodologies. In addition, the short-term vertical profile of reflectivity (VPR) clusters are extensively analyzed to resolve the storm-scale characteristics of different storm cells. The verification results based on independent gauge observations show that both rainfall estimation approaches with dynamic Z - R relations perform much better than fixed Z - R relations. The adaptive approach incorporating the SCIT algorithm and real-time gauge measurements performs best since it can better capture the spatial variability and temporal evolution of precipitation.

Radar and surface station network around the EJRB area

The level-II base data from 16 S-band Doppler weather radars deployed over the EJRB area (Fig. 1a) were temporally matched to construct the Multi Hybrid Mosaic Reflectivity (MHMR) filed on Cartesian coordinates with a horizontal resolution as $0.005^\circ \times 0.005^\circ$. The gauge network in the EJRB area with 4579 surface gauge stations (Fig. 1b) were utilized for fitting the Z - R relationships and verification.

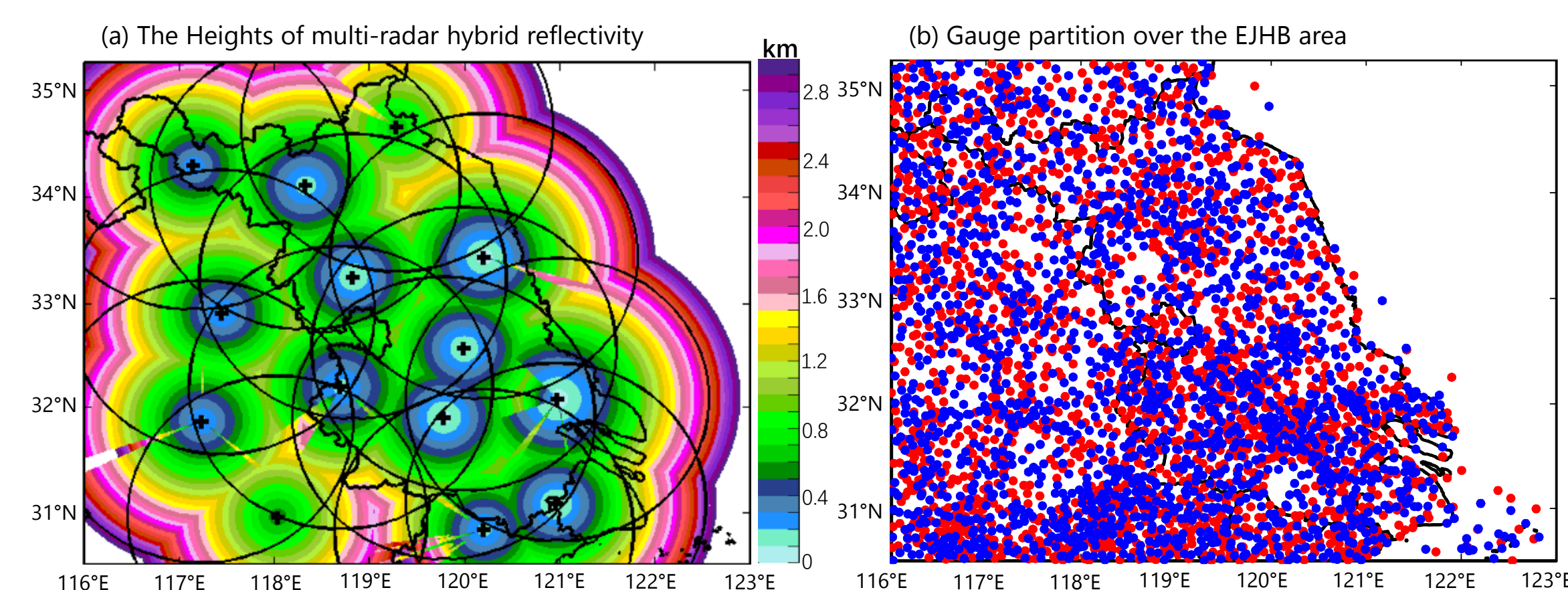


Fig. 1. Radar and gauge network over the EJRB area: (a) 150km radar ranges (black circles) of each radar site and the heights of the MHMR (Multi-radar Hybrid Mosaic Reflectivity) fields; (b) uniform partition of the gauge distribution over the EJRB area. There are 2289 rain gauges in the training dataset (blue) and 2290 rain gauges in the test dataset (red).

Methodologies

Two Z - R relationships fitting scheme (depicted in Fig.2) were used: one used a single global optimal (SGO) Z - R relation, whereas the other was based on the storm cell identification and tracking (SCIT) algorithm.

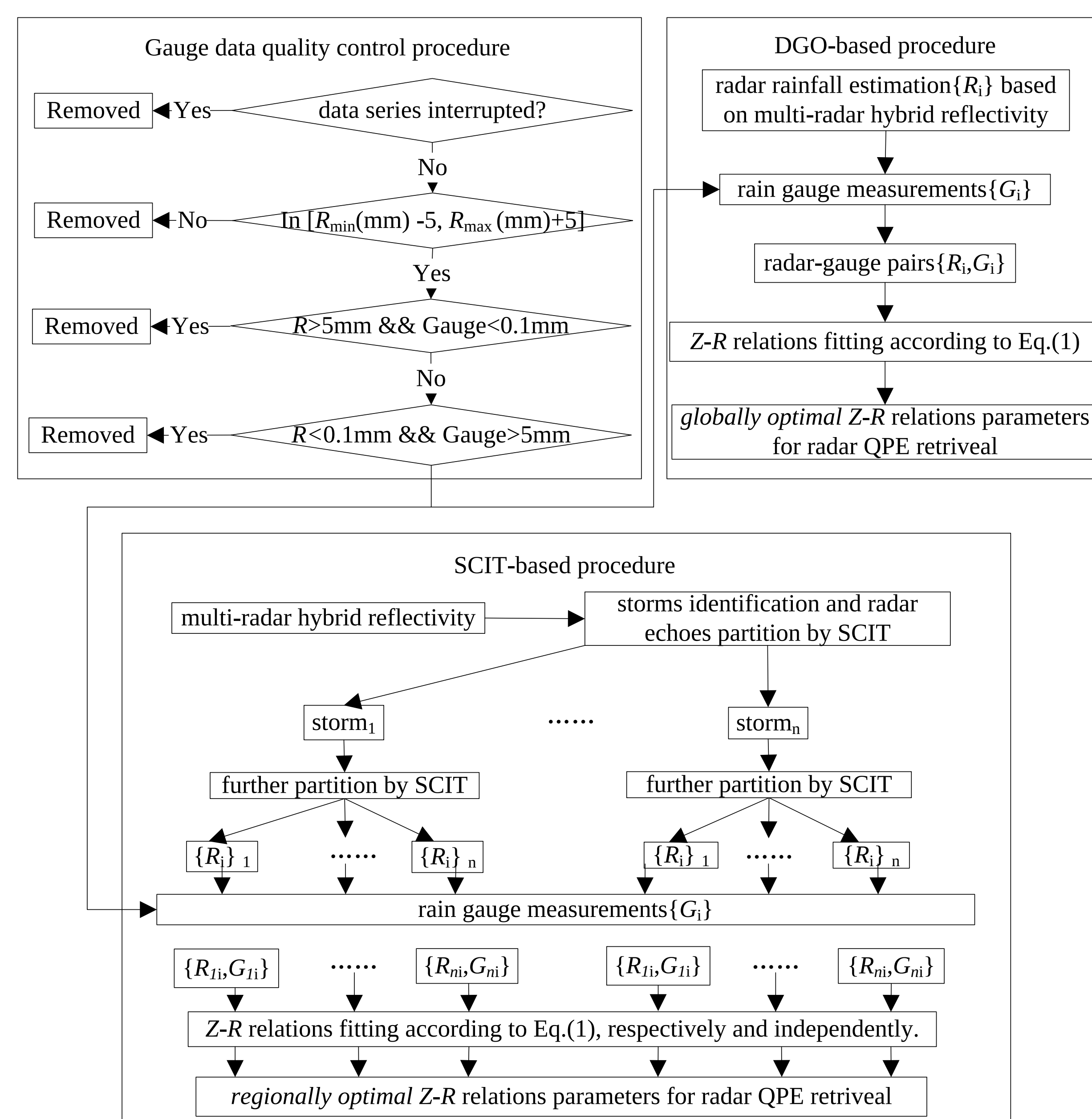


Fig. 2. Flowchart for rain gauge data quality control procedure, SGO-based and SCIT-based procedures.

Case studies

Four precipitation events (depicted in Fig.3) featured by different rainfall microphysical characteristics, which were represented by the storm-scale vertical profile of reflectivity (VPR) clusters, were investigated to demonstrate the performances of the abovementioned two radar QPE methodologies.

The verification results based on independent gauge observations in Fig.1b show that both rainfall estimation approaches with the storm-scale Z - R relations can obtain much better relative error (E_{NMA}), root-mean-square error (E_{RMS}), and Pearson correlation coefficient (E_{CC}) scores than SGO-based Z - R relations (depicted in Fig.5).

Such achievements can be ascribed to that the SCIT algorithm can better capture and represent the spatial variability and temporal evolution of precipitation, therefore, independent storm cells can be matched with different Z - R relationships (as depicted in Fig.6).

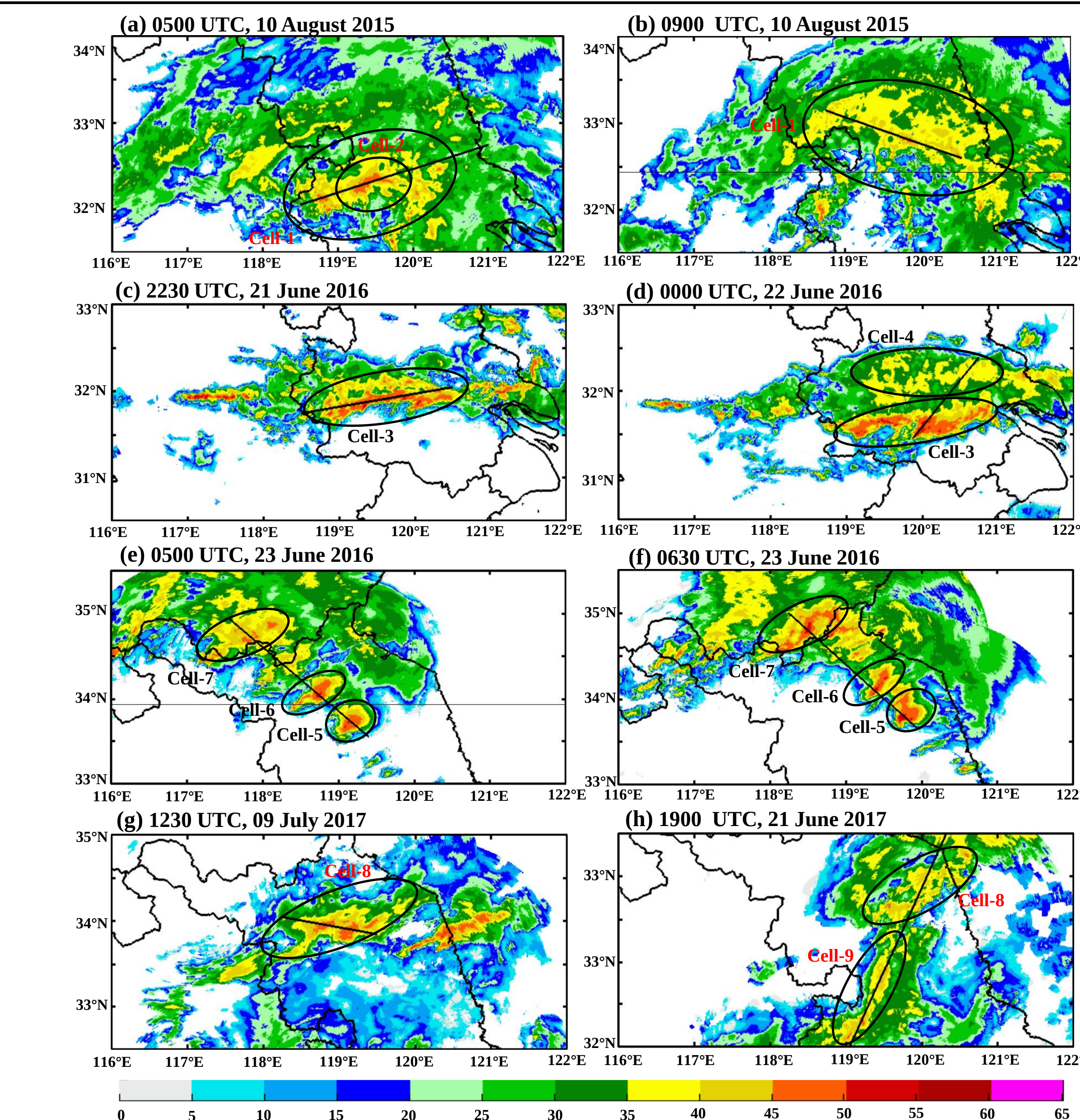


Fig. 3. Storm cells identification results on the MHMR fields at (a) 0500 and (c) 0900 UTC 10 August 2015; (c) 2230 UTC 21 June 2016 and (d) 0000 UTC 22 June 2016; (e) 0500 and (f) 0630 UTC 23 June 2016; (g) 1230 and (h) 1900 UTC 09 July 2017. The circles represent the coverage of nine storm cells and the lines indicate the longitudes and latitudes for the cross-section in Fig. 6.

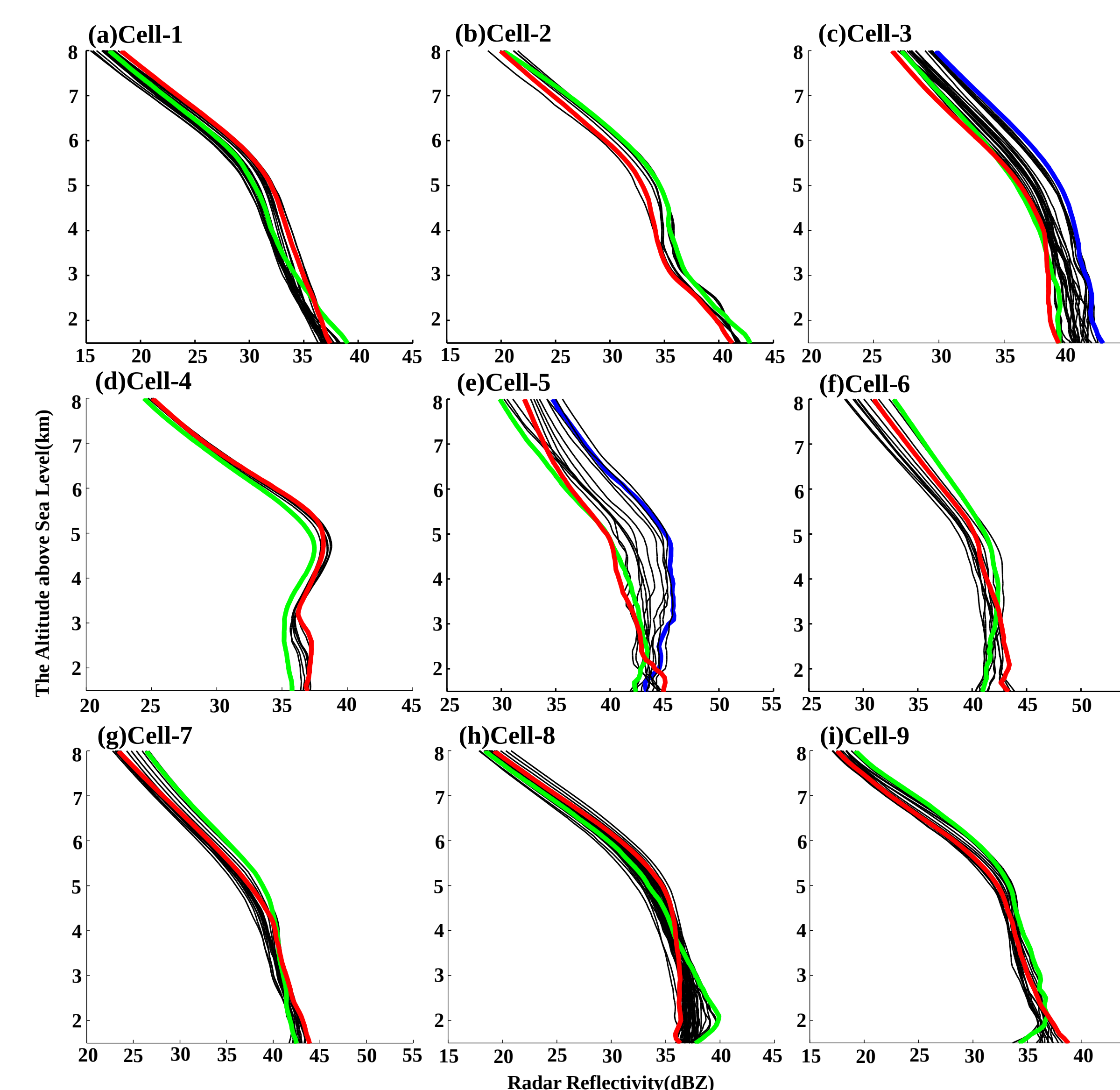


Fig. 4. Storm-scale VPR clusters of nine storm cells in the time intervals listed in Table.3. The green and red curves represent their starting and ending states; the blue curves in (c) and (e) respectively represent the strongest state of cells 3 and 5.

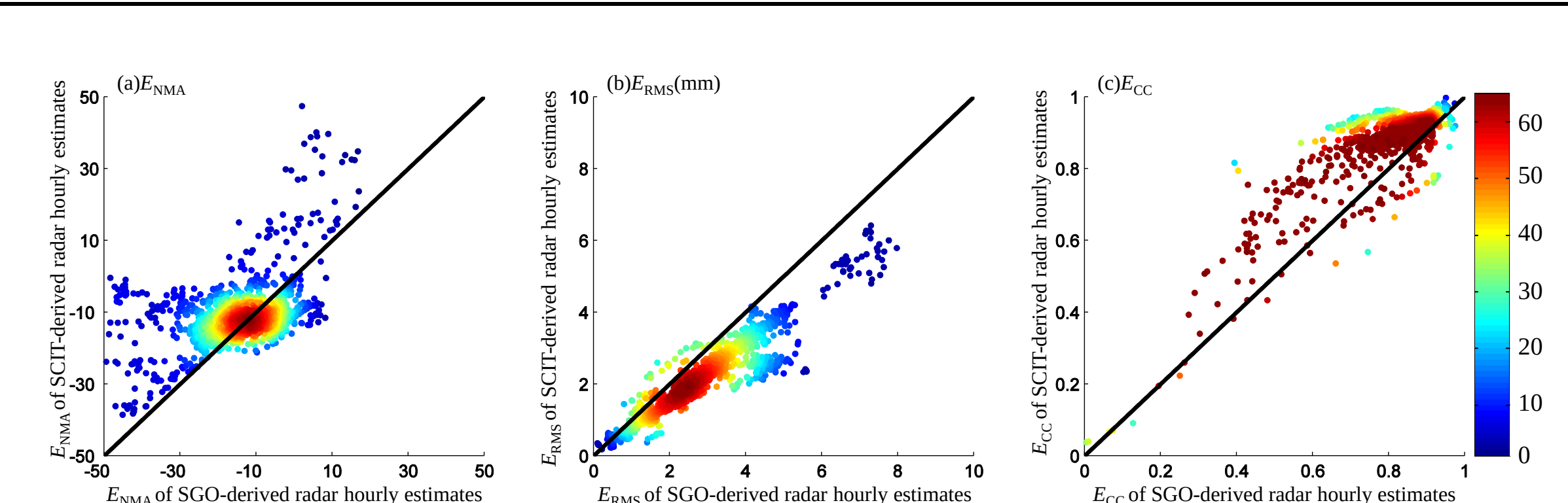


Fig. 5. Comparison of the instantaneous scores of SGO-based and SCIT-based radar QPE algorithm: (a)-(c) are respectively derived from E_{NMA} , E_{RMS} (mm) and E_{CC} .

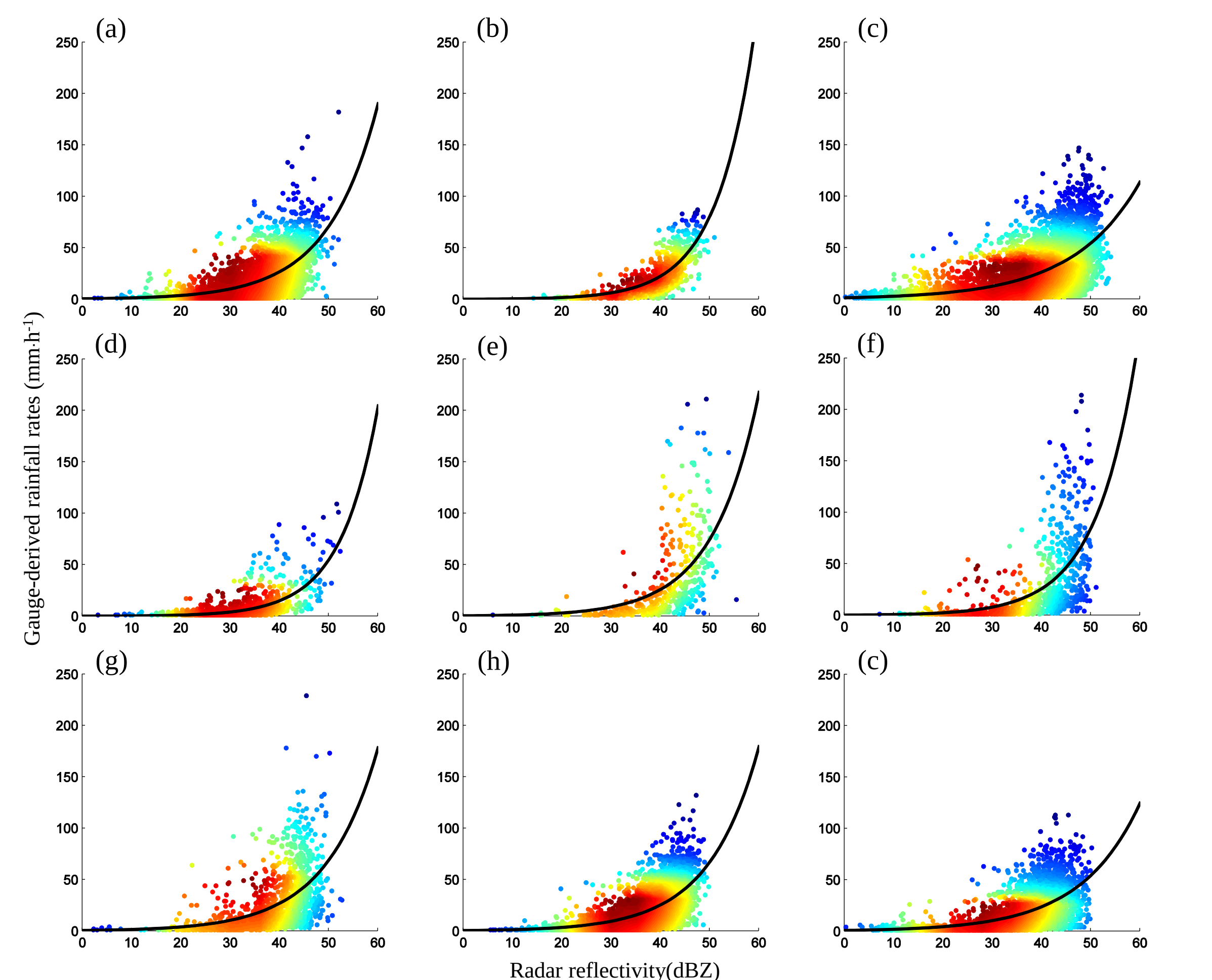


Fig. 6. Gauge-derived rainfall rates versus radar reflectivity within the coverage of nine rainstorms listed in Table. 3: (a)-(i) are respectively related to Cell 1-9 and the black line corresponds to the fitting curve utilizing the radar-gauge dataset.

Summary

The adaptive approach incorporating the SCIT and real-time gauge measurements performs better than the SGO approach. This achievement can be attributed to better representation of the spatial variability and temporal evolution of precipitation of the SCIT approach. Independent Z - R relationships are utilized to demonstrate the parametrized differences during nine rainstorms, which further shows the necessity of the refining more Z - R relationships rather than adopting one single optimal Z - R relationships in the whole coverage of MHMR field.

Acknowledgement

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