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AN ENHANCEMENT TO QUANTITATIVE PRECIPITATION ESTIMATION USING RADAR-GAUGE MERGING (CASE STUDY: EAST JAVA)

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Abstract. Quantitative precipitation estimation (QPE) provides valuable information for hydrology purposes. Its dense spatial and temporal resolution can be combined with surface observations to enhance the accuracy of estimations. This paper presents an enhancement to QPE achieved by adjusting estimation drawn from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) weather radar network at Surabaya, to real-data observations from 58 rain gauges. The Mean Field Bias (MFB) method is used to determine the correction factor through the difference between radar estimations and rain-gauge observation values. The correction factor obtained at each gauge points is interpolated to the entire radar grid in a multiplicative adjustment. Radar–gauge merging results in a significant improvement, revealed by the decreasing of mean absolute error (MAE) and false alarm ratio (FAR) by about 40% as well as increasing the possibility of detection (POD) by more than 50% in all rain categories (light rain, moderate rain, heavy rain and very heavy rain). This performance improvement is likely to provide significant benefits for operational use by BMKG and other hydrological information users.

Keywords: *quantitative precipitation estimation, radar–gauge merging, mean field bias method*

1 INTRODUCTION

The need for rainfall accumulation estimation tools with high-level spatial resolution is growing along with the increasing application of hydrological and weather forecast models. These tools are used widely in water resource analysis, flood forecasting and warnings over sparsely gauged catchments (e.g. Aghakouchak, Habib, & Bardossy, 2010; Zhu, Xuan, & Cluckie, 2014). Accurate accumulation values at tight resolution levels will significantly impact on the performance of these models.

As observation instruments measuring the backscattered power from hydrometeorology particles at particular heights, weather radar can provide estimated values of precipitation at surface levels. Even though such radar have high spatial and temporal resolution, there are still many sources of error that can affect the accuracy of the rainfall estimation values they produce. Sources of error include variation in Z-R relationship, errors in estimating radar reflectivity factor (Wu Hsu, Lien, & Chang, 2015; Wu et al., 2015), difference in radar–gauge sampling (Wilson & Brandes, 1979), natural variability of drop-size distribution, and instrument errors (Joss & Wadvogel, 1990).

The reflectivity observations of radar itself can experience several errors, such as calibration errors, radio emitter interferences and contamination from

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non-meteorological echo, as well as the effect of distance attenuation or increased sampling volume due to beam broadening (Goudenhoofdt & Delobbe, 2009). Uncertainty increases when the estimated rainfall process is being carried out on the surface, resulting from non-uniform vertical reflectivity profile (VPR) and the Z-R relationship. These sources of uncertainty can be minimized by utilizing point data from surface rain-gauge observations, as these have a higher degree of accuracy. Extensive spatial observation range data from radar and accurate point observation data from rain gauges can be combined to enhance the value of estimations.

Radargauge merging has been carried out since the beginning of weather radar operations in the 1970s, and many complex methods have been applied to merge radar and rain-gauge data, including co-kriging (Krajewski, 1987; Sun et al., 2000), objective statistical analysis methods (Pereira Fo, Crawford, & Hartzell, 1998) and Kalman filtering approach (Todini, 2001; Seo & Breidenbach, 2002; Chumchean, Sharma, & Seed, 2006). Before the merging is executed, quality control of the radar data must be carried out, such as elimination of ground clutter, attenuation correction and VPR correction (e.g. Germann, Galli, Boscacci, & Bolliger, 2006; Tabary, 2007; Uijlenhoet & Berne, 2008), because adjustments to uncorrected radar data do not produce significant corrections to QPE. Rain-gauge density is also very influential on the adjustment process, as tested by Sokol (2003) and Chumchean et al. (2006).

The objective of this research is to enhance the accuracy of QPE obtained from weather radar by merging it to surface observations (rain-gauge data) that represent more accurate accumulation values. The final result of this study is expected to be that radar–gaugemerged QPE has better accuracy than radar-only QPE.

2 MATERIALS AND METHODOLOGY

In this study, C-Band single polarimetric radar manufactured by Gematronik Radar with maximum range of 240 km, 250m spatial resolution and nine elevation angles is used (Figure 2-1).

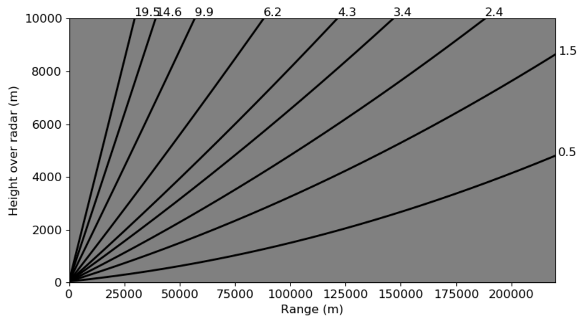


Figure 2-1: Surabaya radar scan strategy

Table 2-1: Radar hardware specification

Parameter	Value
Radar site name	Surabaya
Latitude	-7.41028° S
Longitude	112.76056° E
Altitude	3 m
Tower height	23 m
Frequency	5640 H
Beam width	<1°
Pulse width	0.5–2.0 µs
PRF min	250 Hz
PRF max	1200 Hz
Signal processor	GDRX-SP
Transmitter type	Coaxial magnetron
Polarization	Single
Installation year	2006
Manufacturer	Selex SI Gematronik Radar
Z-R relationship	200 $R^{1.6}$

Radar hardware specification is shown in Table 2-1. The topography around the radar site is variable and contains six volcanoes: Mt. Arjuna, Mt. Kawi, Mt. Bromo, Mt. Ngliman and Mt. Roar. The beam-blockage analysis based on digital elevation data from the SRTM static model is shown in Figure 2-2. The most significant blocking is in the southerly direction, derived from Mt. Arjuna, Mt. Kawi and Mt. Bromo.

2.1 Location and Data

The study area comprises 250 km around Surabaya. The weather radar used covers all of the East Java region, except those areas that are blocked by terrain. Rain-gauge distribution overlaid with beam-blockage analysis at the two lowest elevations is shown in Figure 2-3. There are 145 rain gauges in East Java province that are covered by the radar's maximum observation range, but 34 of these are blocked at 0.5° elevation, and 10 are blocked at 1.5° elevation angle.

Raw data obtained by the Surabaya weather radar with Rainbow5 format is used and calculated to hourly QPE and rewritten to NetCDF format. Full hourly QPE data for the day is then calculated to create the one-day QPE to be adjusted.

In the adjustment process, the rain gauges used are only those that operate for 24 hours, with those that do not cover the full 24-hour period because of instrumentation problems or data-feed issues being excluded.

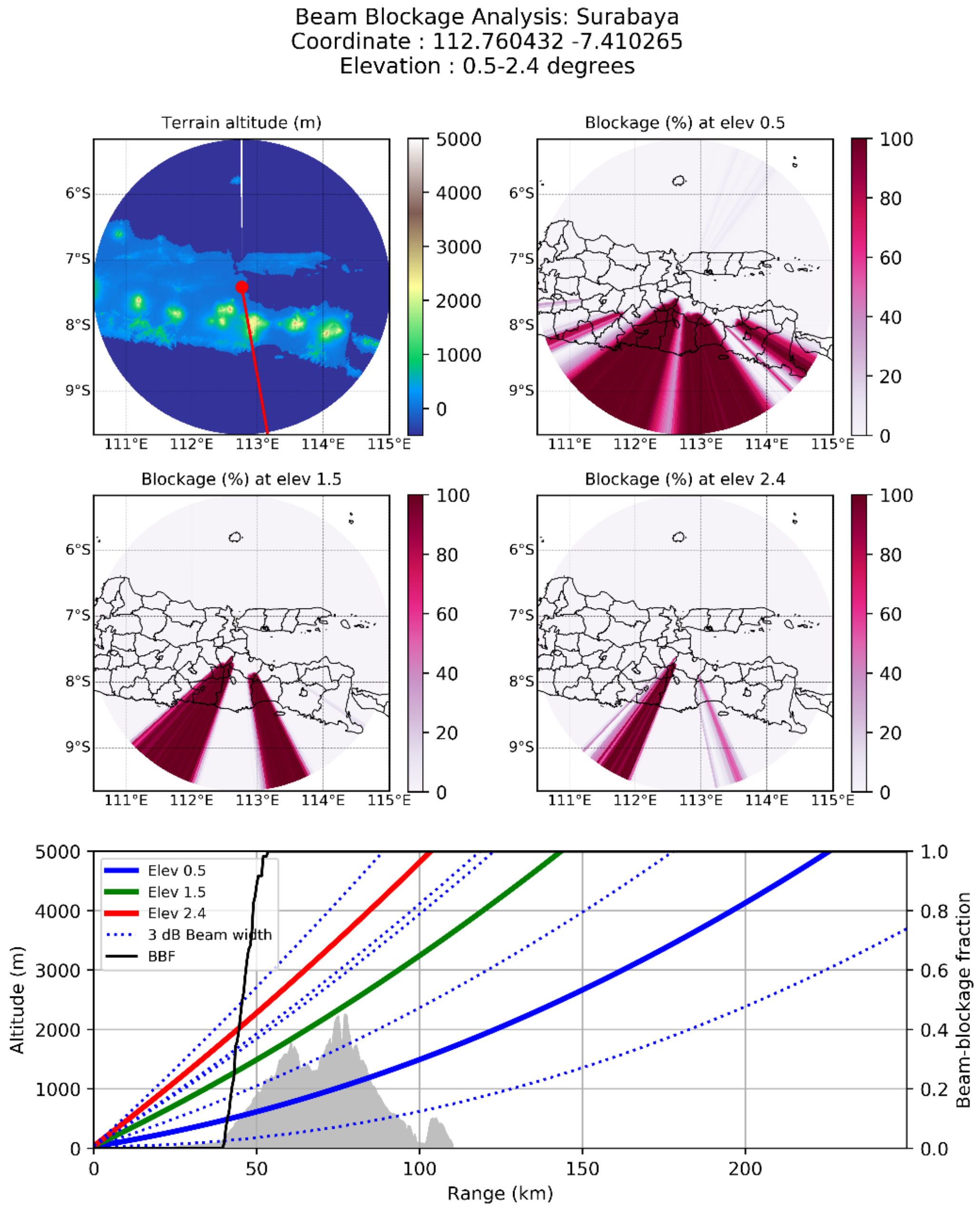


Figure 2-2: Beam-blockage analysis at Surabaya radar.

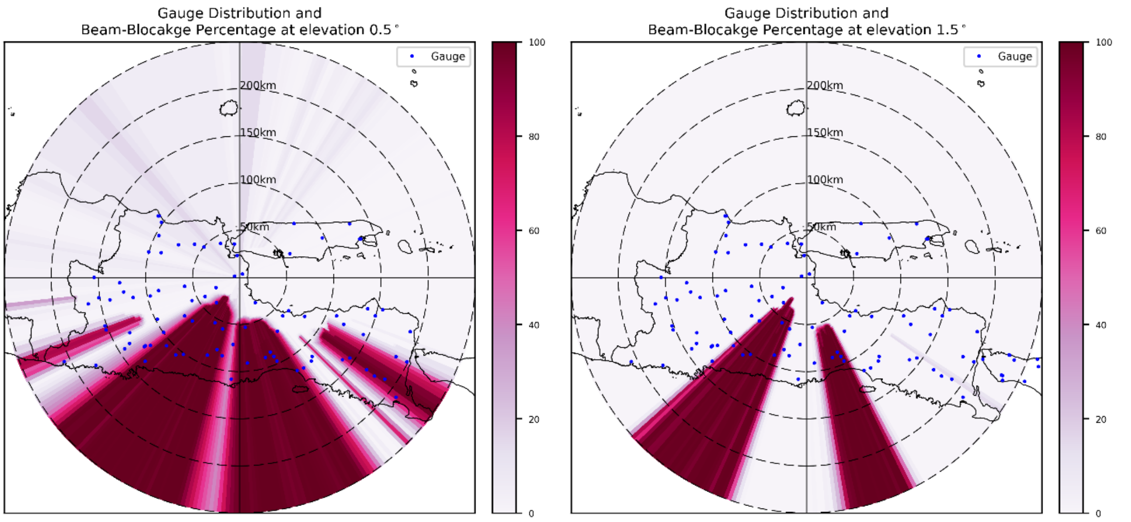


Figure 2-3: Rain-gauge distribution and blockage percentage

Because of the very significant effect of distance on precipitation estimation, this study only uses rain gauges at a distance of up to 150 km from the weather radar. In total, 58 rain gauges were used, and the case studies used are for events detected by weather radar on 17 and 19 March 2019.

2.3 Methods

Several methods have been developed to adjust radar data with rain-gauge data. In this paper, the mean field bias (MFB) method is used. It is important to note the amount of radar data sampling that will be merged with rain-gauge data (Villarini, Mandapaka, Krajewski, & Moore, 2008). In the study by Goudenhoofdt and Delobbe (2009), 9-pixel radar data from around the rain-gauge network was used to represent the value of rainfall accumulation at the corresponding rain-gauge points, and this is the method followed in this study. The use of 9 pixels for the corresponding raingauges can minimize the effect of wind gusts on droplets (Lack & Fox, 2007). The accumulated value used must be more than 1mm both for radar and rain gauges (Goudenhoofdt & Delobbe, 2009).

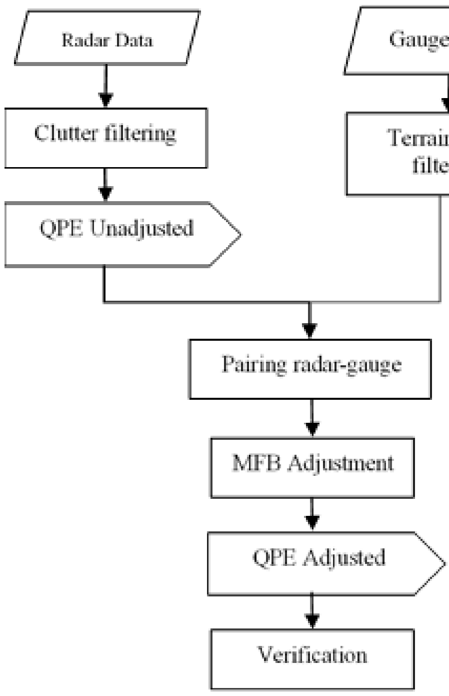


Figure 2-4: Research flowchart

The conversion of reflectivity into rainfall uses the Marshall Palmer Z-R relationship (Equation 2-2) with the input of maximum reflectivity values (Nova, 2017).

$$Z = \int_0^{\infty} N(D)\, D^6 dD \tag{2-1}$$

$$Z = 200\, R^{1.6} \tag{2-2}$$

With Z measured in mm^6/m^3 and R in mm/h. The calculation of hourly QPE is performed using Equation 2-2 (Selex SI, 2017).

Equation 2-3 is used to calculate the QPE from rain intensity obtained from Equation 2-2.

$$A_i = (t_i - t_{i-1}).\frac{R_i + R_{i-1}}{2} \tag{2-3}$$

Where A_i is the accumulation of rain of the i^{th} steps, $(t_i - t_{i-1})$ is the time step (time difference between two consecutive data in hours), and $(R_i + R_{i-1})$ is the accumulation of consecutive data. In one hour, there are six data, since the time difference between consecutive data is 10 minutes. After an hourly accumulation of radar QPE and rain-gauge data are obtained, adjustment is carried out using MFB, with the assumption that radar estimates are affected by a uniform multiplicative error that can result from bad electronic calibration or an erroneous coefficient in the Z-R relationship.

The MFB adjustment factor can be formulated as Equation 2-4:

$$C_{MFB} = \frac{\sum_{i=1}^{N} G_i}{\sum_{i=1}^{N} R_i} \tag{2-4}$$

Where N is the number of radar–gauge pairs, and Gi and Ri are the rainfall values detected by the gauge and radar.

One-hour adjusted QPE is then accumulated for one day and verification is then performed on that one-day data. Verification begins with plotting a correlation graph between the accumulation of radar and rain-gauge data. The quality of the adjustment is measured through the parameter of root mean squares error (RMSE) and mean absolute error (MAE), as shown in Equations 2-5 and 2-6.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(R_i - G_i)^2}{N}} \tag{2-5}$$

$$MAE = \frac{\sum_{i=1}^{N}|R_i - G_i|}{N} \tag{2-6}$$

Contingency table verification is also performed to obtain the possibility of detection (POD), false alarm ratio (FAR), and proportion correct (PC) values for the specified rainfall accumulation category. The accumulation categories refer to the classifications used by BMKG slight rain = 5–20 mm/day; moderate rain = 20–50 mm/day; heavy rain = 50–100 mm/day; and very heavy rain = more than 100 mm/day. The contingency table is presented in Table 2-2, while Equations 2-7, 2-8 and 2-9 show the POD, FAR and PC calculations, respectively. The complete research flowchart is presented in Figure 2-4.

Table 2-2: Contingency table for radar–gauge adjustment

Radar	**Gauge**	
	Yes	No
Yes	Hit (H)	False (F)
No	Miss (M)	Correct negative (N)

$$POD = \frac{H}{H + M} \tag{2-7}$$

$$FAR = \frac{F}{H + F}. \tag{2-8}$$

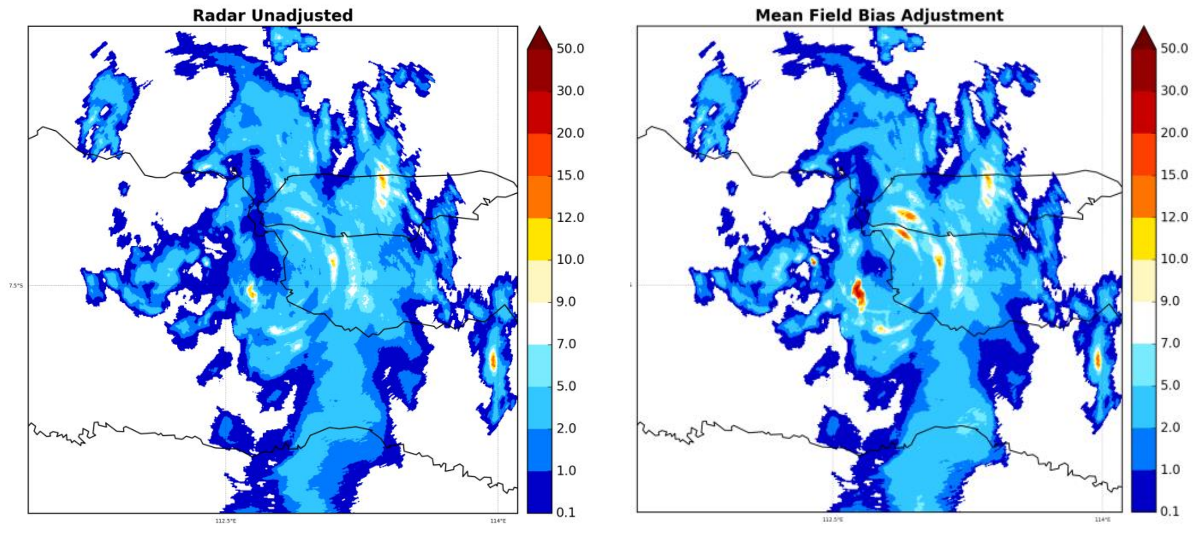
$$PC = \frac{H + N}{H + M + F + N} \tag{2-9}$$

3 RESULTS AND DISCUSSION

Several quality controls were applied to the radar data through the pre- and post-processing tools contained in the Gematronik Radar system, including speckle removal, ground-clutter removal and attenuation correction. Radar data that remains exposed to significant non-meteorological echoes will result in very overestimated QPE, and in such situations, adjustment by gauge itself will have no significant effect. Figure 3-1 presents the results of unadjusted and adjusted one-hour QPE for the first case study on 17 March 2019 at 11 UTC, at which time the most significant rainfall occurred. The calculation of one-day QPE is carried out after the adjustment is performed for each hour's QPE.

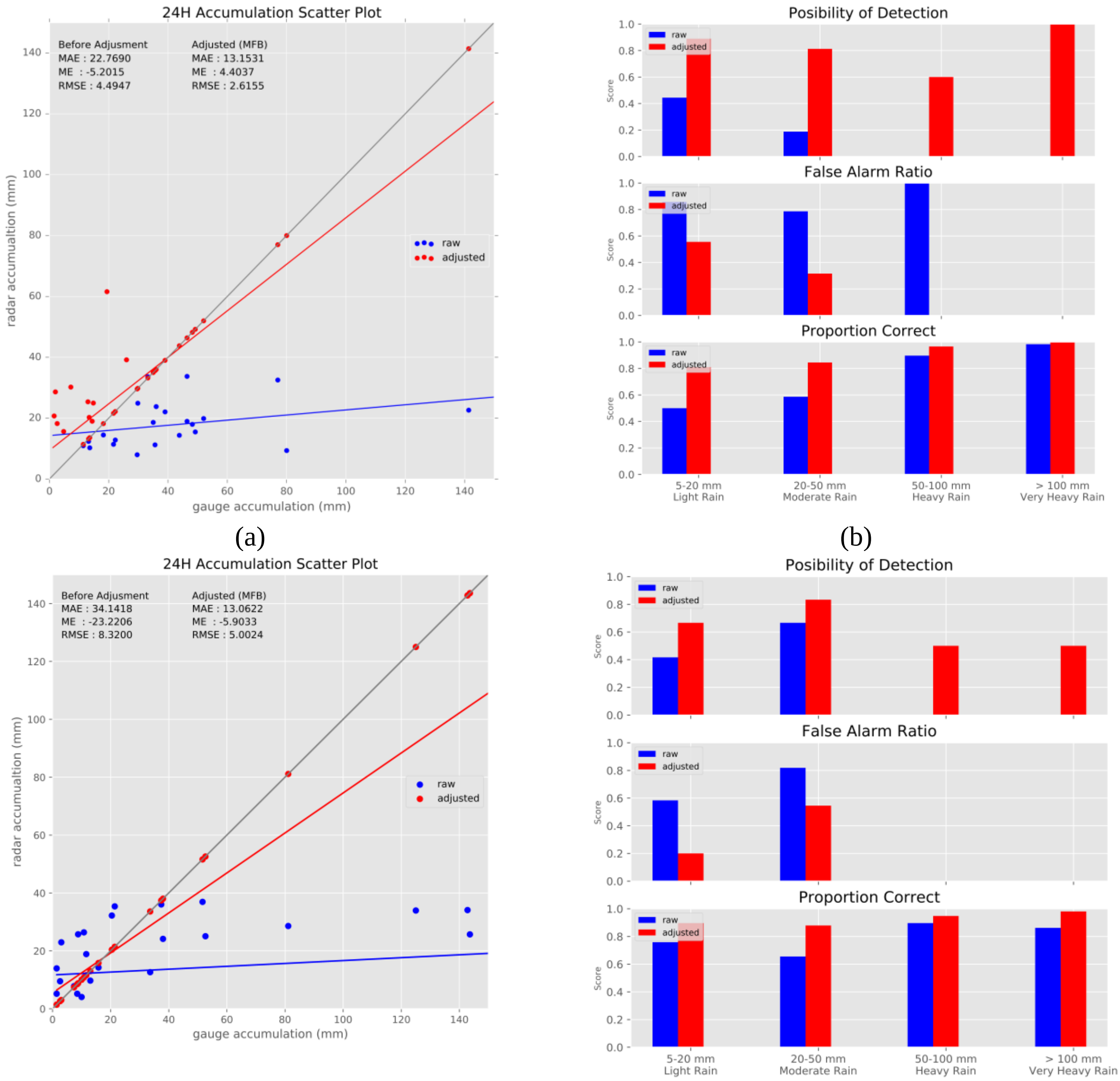
The MFB method does not account for distance as the weighting value to the correction factor, so it will be taken across the entire grid. There is an increasing rainfall accumulation after the adjustment. This increment is adjusted to the hourly gauge accumulation observed. Scatter plot verification at all gauges used (Figure 3-2) shows that radar data without adjustment (raw data) has an underestimated rainfall accumulation, indicated by its fit slope (blue line) being to the right (under) the centre line. This underestimated value is mostly probably caused by an error in Z-R relationship and the absence of differentiation estimation between convective and stratiform rain. After the adjustment is performed, the adjusted-fit slope (red line) shows very significant improvement it approaches the centre line meaning that the estimation is near perfect, though it is still slightly underestimated from the observed accumulation value.

The scale of error value can determine how far the adjustment improves the raw data. After the adjustment for all hours in one day, MAE, ME and RMSE are calculated. For the first case-study day (17 March 2018), the values of MAE, ME and RMSE for the radar data without adjustment are 22.76, 5.20 and 4.49 mm, respectively. After MFB adjustment these values become 13.15, 4.40 and 2.61 mm. Similarly to the first case, the second case (19 March 2019) also shows decreasing error, with MAE, ME and RMSE of 34.14, -23.22 and 8.32 mm, respectively, before adjustment and 13.06, -5.90, and 5.0 after adjustment.



(a) (b)

Figure 3-1: The spatial results of the gauge adjustment at 17 March 2019 11 UTC, when the rain distribution is the most significant: (a) one-hour QPE unadjusted; (b) one-hour QPE MFB adjusted.



(a) (b)

(c) (d)

Figure 3-2: Scatter plot verification at all gauge used. The adjustment results a decreasing error value (a). Scatter plot verification for the first case (17 March 2019) while (c) for the second case (19 March 2019). (b) Contingency verification for the first case while (d) for the second case.

These results indicate that MFB adjustment can give better results in accumulation estimation. The RMSE value after MFB adjustment shows that the standard deviation of the residual between radar and gauge observations is only around 2.6 mm. Estimation accuracy is reinforced by the decreasing value of the MAE. The error value decreases about 40–60% compared to unadjusted radar accumulation (from 22.76 mm to 13.15 mm for the first case, and from 34.14 mm to 13.06 mm for the second case). This is a very good result, indicating that the adjusted radar QPE shows little error at a high spatial resolution.

Contingency table verification is performed for the adjustment process, and the values of POD, FAR and PC before and after MFB adjustment are shown in Figure 3-3. When the radar one-day accumulation value gives the same value as the accumulated rain-gauge data, this is counted as a hit. A value is considered as a miss when the estimation is overestimated or underestimated compared to the selected rainfall accumulation classification. For example, moderate rain is observed by a gauge (accumulation of 30 mm/day) but the radar accumulation estimates more than 50 mm/day or less than 20 mm/day, this will be considered as a miss. POD can represent the radar's ability to detect the specific rainfall classification, while FAR describes how often the radar gives overestimated values.

Before rain-gauge data is merged, the first case gives the value of POD for each category (light rain, moderate rain, heavy rain, and very heavy rain) as 0.45, 0.33, 0 and 0, respectively. After MFB adjustment is applied, the POD values become 0.91, 0.83, 0.6 and 1.0. For the second case, the values of POD for unadjusted QPE at each category are 0.42, 0.67, 0 and 0 and after adjustment become 0.67, 0.83, 0.50 and 0.50.

There are quite large improvements of the POD calculations. The low POD value of unadjusted radar QPE in all rain categories is due to the underestimation of accumulation. There is no successful detection of heavy and very heavy rain events, as shown by the two zero POD values. After the adjustment is performed, all rain classes have more than 0.5 POD. This increment is coupled with PC score and accompanied by decrement in FAR score. Before the adjustment, FAR value for one-day accumulation exceeds 0.85, 0.76, 1.0 and 0 for the first case for each rain category. These values are quite high, and again, underestimation in accumulation is causing this. The decrement is compelling, with the adjustment decreasing FAR scores to 0.57, 0.46, 0 and 0 for light rain, moderate rain, heavy rain, and very heavy rain, respectively. For the second case, unadjusted QPE gives FAR values of 0.52, 0.82, 0 and 0 for each rain category, becoming 0.20, 0.55, 0 and 0 after adjustment.

4 CONCLUSION

The results of the rain-gauge adjustment to the hourly radar QPE and continued to the one-day QPE show significant incremental improvement in performance. Although the adjustment method does not take into account the distance of rain gauges from the radar pixels, the error value can be reduced significantly, by approximately 40%. The performance also improves more than 50% in all rain categories. The number and density level of rain gauges also significantly affects the correction process, with higher density of the rain-gauge network providing more significant correction. The presence of the rain-gauge selection filter is also influential on the adjustments. It is necessary to carry out further research into adjustment methods by taking into account rain-gauge distance to the radar pixels.

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AUTHOR CONTRIBUTIONS

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