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Modified mean field bias and local bias for improvement bias corrected satellite rainfall estimates

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सार – वर्षा के उपग्रह से लिए गए आकलनों में सुधार करने के लिए प्राय: संशोधित बायस का प्रयोग किया जाता है। सबसे तेजी के साथ संशोधित किए गए बायस की पद्धति मीन फील्ड बायस (MFB) और लोकल बायस (LB) हैं। फिर भी प्रेक्षित की गई वर्षा और उपग्रह से लिए गए वर्षा के आकलनों के अनुपात का प्रयोग करते हुए TRMM जैसे आकलन वर्षा की किसी भी प्रकार की स्थितियों के प्रति असावधानी नहीं बरतती है। जबकि उष्णकटबंधीय मेरी टाइम क्षेत्र में वर्षा का न होना प्राय: होता है। इस अध्ययन का उद्देश्य MFB और LB के अनुपात का उपयोग करते हुए वर्षा के उपग्रह के आकलनों के संशोधन में सुधार लाने पर ध्यान केंद्रित करना है। जबकि प्रतिलोमन दूरी पद्धति का उपयोग करते हुए अनुपात को इंटरपोलेटेड करने से पहले स्थानीय बायस के अनुपात को वर्गीकृत किया गया। इस विवेचन को अमल में लाने के लिए मकासर जलसंधि के आस-पास के वर्षा के आंकड़ों को लिया गया है। वर्षा के न होने की स्थिति में अनुपात के निष्फल होने से बचने के लिए वर्षा के आंकड़ों में 1 मि. मी. जोड़ा गया। इस विवेचन का मूल्यांकन वर्ग मूल औसत त्रुटि (RMSE) औसत निरपेक्ष त्रुटि (MAE) और सहसंबंध के साथ किया गया है। इन परिणामों से यह पता चलता है कि परिष्कृत लोकल बायस का निष्पादन RMSE और MAE में सुधार ला सकता है। सहसंबंध के मानों के आधार पर 20 क्लासों सहित परिष्कृत LB कंडीशनल मर्जिंग (CM) को छोड़कर अन्य पद्धतियों की अपेक्षा सहसंबंध को बढ़ा सकता है। हालांकि RMSE में MFB की अपेक्षा LB की पद्धति ज्यादा अच्छी है। पर यह CM से कहीं अधिक खराब है। फिर भी MAE के स्थायित्व की वजह से वर्षा के उपग्रह से प्राप्त हुए आकलनों के लिए LB सर्वश्रेष्ठ संशोधन पद्धति हो सकती है। इस परिष्कृत अभिपुष्टि से यह समझ में आता है कि वर्षा की घटना के होने या नहीं होने की बात उपग्रह से प्राप्त वर्षा के आकलनों को प्रभावित करता है।

ABSTRACT. Corrected bias is often used to improve satellite rainfall estimates. The fastest corrected bias methods are mean field bias (MFB) and local bias (LB). Nevertheless, using the ratio between rainfalls observed and satellite rainfall estimates such as TRMM neglects no rain conditions. Whereas zero rainfall often happens in the tropical maritime region. The aim of this study focuses on improvement of correcting satellite rainfall estimates in using the ratio of MFB and LB. Modified MFB is done by classifying the ratio, then multiplied it to the pixel of TRMM rainfall estimates. While, classified the ratio of local bias is done before interpolated the ratios uses inverse distance methods. Implementation of this treatment uses rainfall data in surrounding of the Makassar Strait. For avoiding of failure of a ratio in zero rainfall observed, 1 mm is added to the rainfall data. Evaluation of this treatment is assessed by root mean square (RMSE), mean absolute error (MAE) and correlation. The result shows that performance modified local bias (LB) can improve RMSE and MAE. Based on value of correlation, modified LB with 20 classes can increase correlation than other methods except conditional merging (CM). Although LB is better methods than MFB in RMSE, but it is worse than CM. Moreover, modified LB can be considered as the best correction method for satellite rainfall estimates because of the stabilization of MAE. This modified, affirm assumed that the persistence of rainfall event or not, have an effect of satellite rainfall estimate performance.

Key words – Corrected satellite rainfall estimates, Tropical maritime, Sulawesi, Modified.

1. Introduction

The availability of precipitation data in satisfactory spatial distribution is difficult to provide for hydrological needs (Goovaerts, 2000; Jia *et al*., 2011). Rainfall data mainly derived from three sources. There are the direct rainfall measurement from rain gauge stations, rainfall estimation from remote sensing such as satellite and rainfall estimates from weather model. Although a rain gauge station measures direct precipitation and it is expected the most accuracy, but it restricted in numbers and poor in the spatial distribution. Hence, researchers use spatial interpolation to estimate rainfall in ungauged location (Keblouti *et al*., 2012; Das *et al*., 2017).

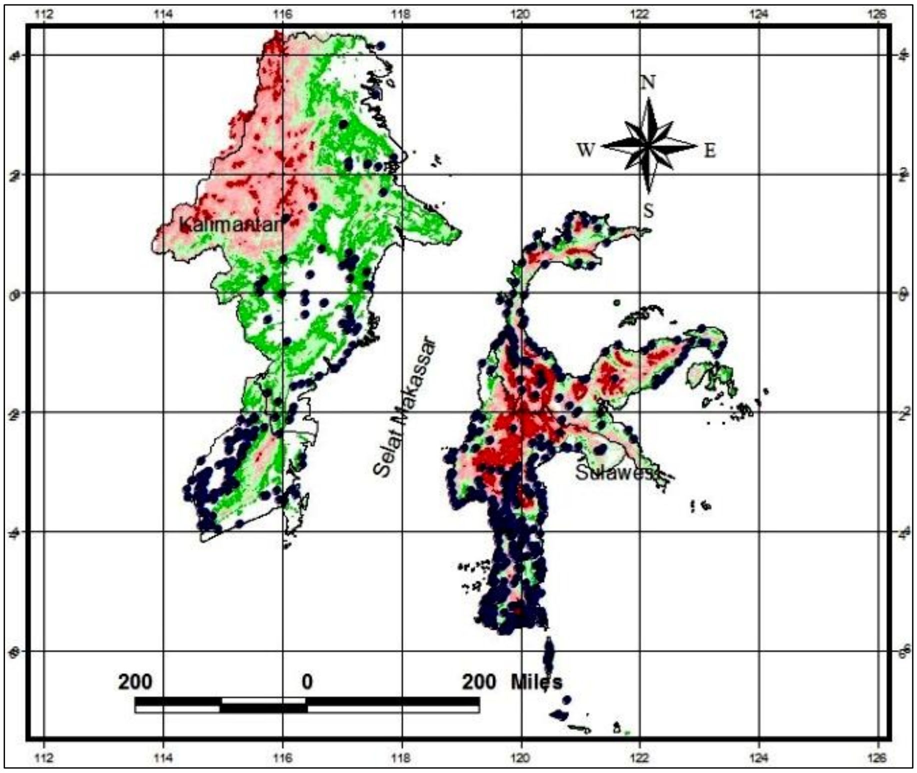

Fig. 1. Locations of rain gauge (blue circles) in surrounding the Makassar Strait, Kalimantan (western) and Sulawesi (eastern). Sulawesi has more mountains (red colour) than Kalimantan, while Kalimantan is dominated by terrain below 1000 meters (green and white colour)

Meanwhile, the others combine different types of rainfall data from various types of measurement techniques (Sik *et al*., 2007; McKee, 2015). Hence, this technique takes the advantages of both types of rainfall data to predict rainfall in a location.

The combination of different types of rainfall data can improve accuracy of rainfall estimation compared with only remote sensing rainfall estimates (Kim *et al*., 2008; Goudenhoofdt and Delobbe, 2009; Mitra *et al*., 2009). The fastest method of combination of different types, uses the ratio between rainfall observed and remote sensing rainfall estimates (McKee, 2015; Mahavik, 2017). The ratio can be in a single value that applied in all areas or multiplies interpolation result of local ratio to rainfall interpolated. The first is called mean field bias (MFB) and the second is a local bias adjustment (LB). Some researchers restricted only consider in above 1 mm rainfall case, especially corrected rainfall in heavy rain (Goudenhoofdt and Delobbe, 2009; Mahavik, 2017). Therefore, they neglect ratio of zero value of rainfall in the interest area.

In the tropical region include Indonesian maritime continent (IMC), rainfall event is very random. Then, the rainfall in this region can be varied in a short time and also although in close location. Some places may have a high rainfall accumulation, but the other places have zero rainfall accumulation. This condition makes a lot of zero rainfall in daily accumulation found, although in the rainy season. The local factors such as sea or mountain breeze can influence of rainfall in a location (Qian, 2008; Hashiguchi *et al*., 2013). Combining with global weather global circulation through in this region makes rainfall in a location is not similar in each place in Indonesia (D'Arrigo and Wilson, 2008; Giarno *et al*., 2012; Lee, 2015).

Using directly correction methods in this area that neglects zero rainfall is not suitable because it will ignore the large amount of rainfall data. Moreover, accuracy of satellite rainfall estimates varies both in the Indonesian maritime continent (Prasetya *et al*., 2013; Giarno *et al*., 2018) and in other places such as Bangladesh (Rahman *et al*., 2012), Himalaya (Parida *et al*., 2017), Cina (Tang *et al*., 2016), Iran (Sharifi *et al*., 2016), Korea, Jepang (Kim *et al*., 2017) and Singapura (Tan and Duan, 2017). Rainfall at a location sometimes can't represent to close locations, so weighting using general ratio neglects local variability. Hence, it may be not suitable to correct

TRMM rainfall estimates in local scale, mainly in IMC region. So that it must be modified. Moreover, using zero rainfall observed in ratio, will make the failure of weight. So, this work tries improvement corrected the TRMM rainfall estimates by treatment of the ratio.

2. Data and method

2.1. *Study area*

Surrounding of the Strait of Makassar is chosen in this study. This region is located between 113.875° E - 123.625° E and 7.625° S - 4.125° N. There are two big islands in surrounding of this strait, Kalimantan Island and Sulawesi Island. Also, some sea encompasses this region in the north and the south such as the Java Sea, the Sulawesi Sea and the Flores Sea. Meanwhile, in the east part of this region, Kalimantan Island is a flatter land than Sulawesi Island, which it's elevation does not reach 1000 m. On the contrary, in the western part of the strait is Sulawesi Island that has mountainous region. Where it has complex topography.

Besides Asian Monsoon and Australian Monsoon as the most influential of rainfall event in IMC region, the other factors that influence to rainfall event are El Niño and the Southern Oscillation (ENSO), Madden-Julian Oscillation (MJO, Indian Ocean Dipole (IOD) (D'Arrigo and Wilson, 2008; Hidayat and Kizu, 2010) or local circulation such as sea and mountain breeze (Hashiguchi *et al.*, 2013). That makes each region has an own early time of rainfall and withdrawal (Giarno *et al*., 2012).

2.2. *Data*

Rainfall data in Indonesia are measured and collected by the Indonesian Meteorological Institute (BMKG) where the location of the rain gauge is distributed as shown in Fig. 1. The higher density of rain gauge in Sulawesi Island than Kalimantan Island, also is in the south part of Sulawesi Island than the north part. In this work used 589 rain gauge locations in 2015. Where 544 locations are used for the correction bias of satellite rainfall estimates and 45 locations randomly chosen for validating the correction (Table 1). Independent rainfall observed is needed to evaluate performance of correcting the TRMM rainfall estimates (Mitra *et al*., 2013).

There are only less than 30% of the places in this region have rainy days in 2015. Very light rain event (0-5 mm/day) dominates a rainfall event. There is very little rainfall in the peak of the dry season such as in

TABLE 1

Independent locations of rain gauge for validating rainfall bias corrected

S. No.	Name Location	Long. (°)	Lat. (°)	Height (m)
1.	Cerbon Sei Rasau	-3.045	114.753	6
2.	Banua Hanyar	-2.454	115.165	7
3.	Langkang Baru	-3.950	116.069	28
4.	Lontar	-3.798	114.781	16
5.	Sengayam	-3.981	116.193	15
6.	Pabahanan	-2.731	115.338	30
7.	Samhurang	-2.616	115.237	134
8.	Pudi Seberang	-2.880	116.340	7
9.	Angsana Indah	-3.713	115.602	16
10.	Manunggal Lama	-2.530	116.000	10
11.	Upau Masingai'i	-2.103	115.553	62
12.	Tenggarong	-0.160	116.719	17
13.	Tenggarong Seb	2.164	117.456	29
14.	Rempanga	-0.503	117.015	16
15.	Long Iram	0.010	115.644	86
16.	Bengalon	0.683	117.119	118
17.	Sangkulirang	-0.987	117.981	1
18.	Bukit Makmur	2.111	117.122	60
19.	Harapan Jaya	2.197	117.130	700
20.	Nunukan	0.137	117.667	8
21.	BPP Bahagia	-1.146	120.103	579
22.	Watatu	-0.873	119.585	20
23.	Tivo	1.300	120.628	3
24.	Lais Ogoasang	0.779	120.449	3
25.	Ds Beringin	-0.873	122.219	59
26.	Sinorang	-1.382	122.446	6
27.	Baji Minasa	-5.499	120.073	9
28.	BPP Amali	-4.404	120.110	125
29.	BPP Lanca Tellu	-4.384	120.239	52
30.	Awangpone	-4.497	120.347	9
31.	Pg Camming	-4.859	120.093	132
32.	Bontotanga	-5.440	120.350	144
33.	BB Garing	-5.442	119.842	300
34.	BPP Sukamaju	-2.540	120.480	28
35.	Stamar Paotere	-5.114	119.420	2
36.	BPP Tanralili	-5.066	119.620	18
37.	BPP Marang	-4.780	119.940	189
38.	Lampa	-3.661	119.533	7
39.	SMPK Tiroang	-3.829	119.741	20
40.	Watan Pulu	-3.905	119.742	19
41.	BPPK Galesong	-5.316	119.386	15
42.	Cakura	-5.425	119.511	20
43.	Rantebua	-3.090	119.986	784
44.	AAWS Bontouse	-4.046	120.031	15
45.	BPP Manyili	-4.179	120.285	16

August, September and October. In those months, no rain event reaches more than 90%. On the contrary, the rain season in this year, rainfall event is not so dominant. The peak of rainfall happens in December, January and February when the moist air from the Asian monsoon is dominant cause rainfall in this region, mainly in the south.

Rainfall observed is considered the best data, then it will be used to correct the TRMM rainfall estimates. The daily rainfall estimates of TRMM product is available at ftp://disc2.nascom.nasa.gov/data/TRMM/Gridded/). Although satellite rainfall products are not particularly accurate because of the spatial scale effect, daily resolution and the island complexity (Rahmawati and Lubczynski, 2017), but in some parts of Asia show that TRMM rainfall estimates better than others (Rahman *et al*., 2012; Hu *et al*., 2014). So this satellite rainfall product is chosen to combine with rainfall observed from land stations.

Combination rainfall observed from rain gauge and satellite rainfall estimates is done in daily. The missing data are neglected and deleted each day because highly dynamical of weather circulation in this region. Correction of satellite rainfall estimate uses rainfall observed on the same day.

2.3. *Bias corrected methods*

There are two classes of correction methods for the rainfall of remote sensing estimates, error variance minimization and bias reduction (Wang *et al*., 2013; McKee, 2015). Minimization of error variance takes advantage of interpolation of error as a correction (Sinclair and Pegram, 2005; Goudenhoofdt and Delobbe, 2009). While bias reduction uses one coefficient that multiplied as correction of rainfall estimation of remote sensing (Sik *et al*., 2007). Moreover, correction can be done in general or local correction, although this method is not always a good result in some places (Sik *et al*., 2007; Goudenhoofdt and Delobbe, 2009), but it can be the best correction methods in the tropical region such as Thailand (Mahavik, 2017).

2.3.1. *Mean field bias (MFB)*

Mean field bias or MFB corrects TRMM rainfall estimates or other remote sensing rainfall estimates using the ratio, then multiplies it to each pixel of remote sensing rainfall estimates. The ratio obtained from comparison between rainfall observed and rainfall remote sensing estimates. The nearest pixel of rainfall of remote sensing is chosen in each rain gauge location. Then, the total of rain observed divided by the total of remote sensing rainfall estimates as correction using the following equation:

$$C = \frac{\sum_{i=1}^{N} G_i}{\sum_{i=1}^{N} R_i} \tag{1}$$

where, C is MFB correction, G is rainfall observed on the ground, R is rainfall estimate of remote sensing, i is rain gauge location and N is number of rainfall station observation on the ground. Corrected factor C is then applied in the entire spatial domain of remote sensing of interest.

2.3.2. *Local bias (LB)*

MFB uses one ratio that is applied to entire pixel of remote sensing rainfall estimates, so that difference of rainfall observed in a location and satellite rainfall estimates is not considered. Therefore local bias or LB is used. Ratio is calculated in each rain gauge location, then interpolates its whole interest of the area. Corrected in equation (1) is calculated in each location.

$$C_i = \frac{G_i}{R_i} \tag{2}$$

Recorded zero rainfall is common in the tropical Indonesian maritime continent region, although in rainy season. Applied equation (2) directly will result an error correction factor. Hence, only the pairs exceeds 1 mm are considered (Delobbe *et al*., 2008). But, removing a location which has zero rainfall means ignoring the fact that there is a part of the area that does not rain. So in this work, locations which has zero rainfall are still used, but modified by adding 1 mm to avoiding giant divisor. After calculating local correction factor in each location, then it is interpolated in the entire area of interest. The inverse distance weighting is used to interpolate method because of simple and fast in the calculation. Then, the interpolation result of correction factor is multiplied to TRMM rainfall estimates.

2.3.3. *Modified correction by classification*

Satellite rainfall estimates such as TRMM tends overestimate than in rainfall observed (Ochoa *et al*., 2014; Kneis *et al*., 2014). Sometimes the difference between TRMM rainfall and observation rainfall is very large. So that it can result giant ratio. For this reason, it is necessary to classify the ratio. The Classifying the ratio can be used to anticipate a giant correction factor. Moreover, in this

TABLE 2

Comparison corrected TRMM rainfall estimates CM, mean field bias (MFB), local bias (LB) and the modified in 8, 9 and 20 classes

Method/Indicator	Correlation			RMSE			MAE		
	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
Trmm	0.16285	0.91957	-0.25466	13.23318	39.23360	0.00000	7.08595	21.26715	0.00000
MFB_mean	0.01409	0.68869	-0.32477	19.49109	47.38728	12.81286	12.10074	25.28402	7.53909
MFB_sum	0.01409	0.68869	-0.32477	19.49109	47.38728	12.81286	12.10074	25.28402	7.53909
MFB_8class	0.01450	0.68869	-0.32477	16.14459	49.21500	0.00000	9.71127	25.46690	0.00000
MFB_9class	0.01450	0.68869	-0.32477	16.14459	49.21500	0.00000	9.71127	25.46690	0.00000
MFB_20class	0.01450	0.68869	-0.32477	18.16857	46.10915	0.00000	11.13316	26.27302	0.00000
LB	0.14935	0.99789	-0.22132	15.17275	78.88354	0.00000	7.40768	32.21194	0.00000
Local Bias_8class	0.15634	0.98109	-0.23250	11.44032	47.68220	0.00000	5.34286	22.98433	0.00000
Local Bias_9class	0.15636	0.98109	-0.23258	11.44006	47.68248	0.00000	5.34213	22.98466	0.00000
Local Bias_20 class	0.16331	0.98714	-0.22929	11.41270	40.37668	0.00000	5.41220	20.24909	0.00000
CM	0.28231	0.99702	-0.26399	10.71762	104.52520	0.01546	6.14314	31.12116	0.00604

work resulted correction factor in the equation (2) will be classified in 9 classes as below:

$$\left.\begin{array}{ll} 0 < C_i \le 1 & ;C_i = 1 \\ 1 < C_i \le 2 & ;C_i = 1/2 \\ 2 < C_i \le 5 & ;C_i = 1/5 \\ 5 < C_i \le 10 & ;C_i = 1/10 \\ 10 < C_i \le 20 & ;C_i = 1/20 \\ 20 < C_i \le 30 & ;C_i = 1/30 \\ 30 < C_i \le 50 & ;C_i = 1/50 \\ 50 < C_i \le 100 & ;C_i = 1/100 \\ 100 > C_i & ;C_i = 1/150 \end{array}\right\} \quad (3)$$

Correction factor that obtained from the equation (3) is interpolated using IDW in an entire interest area, then the result is multiplied with estimation of TRMM. Besides 9 classes, in this work also calculates 8 and 20 class as compared.

2.3.4. *Conditional merging (CM)*

In this study we include conditional merging (CM) that is often considered the best in combining rainfall data from rain gauge and remote sensing rainfall estimates (Sik *et al*., 2007; Goudenhoofdt and Delobbe, 2009; Park *et al*., 2017). Sinclair and Pegram (2005) are considered as the first ones that found this method (McKee, 2015). This method assumes that remote sensing rainfall estimates such as TRMM has a true field of unknown values, while the rain gauges produce an unknown field of true values. The CM combines the strengths of each technique using following equation

$$\left.\begin{array}{l} Z(s) = I_G(s) + \varepsilon_G(s) \\ R(s) = I_R(s) + \varepsilon_R(s) \\ M(s) = I_G(s) + \varepsilon_R(s) \end{array}\right\} \quad (4)$$

where, $Z(s)$ is the true rainfall field at location *s*, $I_G(s)$ is rainfall interpolation of $Z(s)$ from the rain gauge and $\varepsilon_G(s)$ is error of $I_G(s)$. $R(s)$ is the remote sensing rainfall estimates at location *s*, $I_R(s)$ is rainfall interpolation of $R(s)$ using the remote sensing values and $\varepsilon_R(s)$ is error of $I_R(s)$. Finally $M(s)$ is the corrected rainfall estimates and *s* is a location.

Improved rainfall estimates with CM has longer steps than MFB and LB. First, TRMM rainfall estimates in each gauge location are selected and interpolated in the whole area of as interest. Second, the difference between interpolation and original TRMM estimation is calculated. Third, rainfall observed is interpolated in an area that same with TRMM area of interest as correction of rainfall in each grid. Finally, the result of interpolation is added with a difference of interpolation and original TRMM rainfall estimates.

CM result contains two error sources. There are an error from gauge interpolation and satellite interpolation. Because of TRMM tends to overestimate prediction, the value may be negative. If the error is too large, corrected rainfall estimates will have big negative rainfall. Of course, it is an unreasonable condition for rainfall measurement. So in this work, all negative of the rainfall correction result is replaced by zero.

In this work, we modified CM by using an inverse distance weighting (IDW) than the original CM that always uses the kriging. A lot of zero of daily rainfall in the tropical region, so that this condition makes the using of a kriging very difficult and often unsuccessful for semivariogram modelling.

2.4. *Evaluation method*

Satellite rainfall estimates is corrected in daily, so do the evaluation. In this work, evaluation uses three statistic indicators. There are pearson coeficient correlation (*r*), root mean square error (RMSE) and mean absolute error (MAE) that formulated as

$$r = \sqrt{\left[\frac{\sum_{i=1}^{n}\left(G_i - \overline{G}_i\right)\left(CSE_i - \overline{CSE}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(G_i - \overline{G}_i\right)^2}\sqrt{\sum_{i=1}^{n}\left(CSE_i - \overline{CSE}_i\right)^2}}\right]^2} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(G_i - CSE_i\right)^2}{n}} \quad (6)$$

$$MAE = \frac{\sum_{i=1}^{n}\left|G_i - CSE_i\right|}{n} \quad (7)$$

where, G_i refers to rainfall observed, $\overline{G_i}$ refers to average of G_i. While CSE_i refers to corrected satellite result and $\overline{CSE_i}$ refers to average of CSE_i. Then refers to total of rain gauge station and *i* refers to station index.

This evaluation was conducted using rainfall from 45 different locations with the location which used for correction of satellite rainfall estimates. Correlation, RMSE and MAE are calculated on daily at each 45 locations and simplified evaluation is shown in a table and boxplot. Besides showing the median, first and third quantile, the bloxplot will also show distributed in minimum and maximum of evaluation parameter.

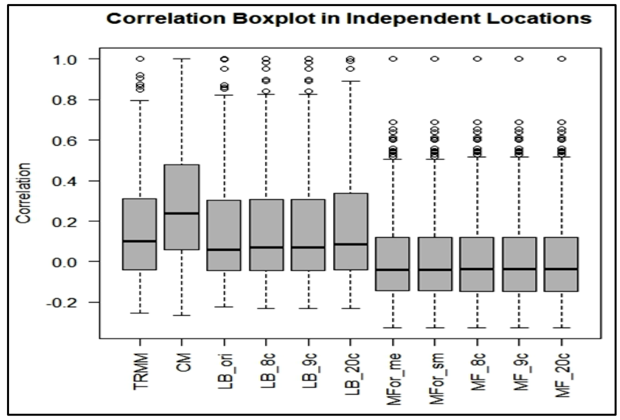

Fig. 2. Correlation in bloxplot of TRMM rainfall estimates, conditional merging (CM), original local bias (LB_ori), modified local bias with 8, 9 and 20 classes respectively LB_8c, LB_9c and LB_20c, mean field bias with mean (MFor_me), mean field bias with summation (MFor_sum) and modified mean field bias with 8, 9 and 20 classes respectively MFB_8c, MFB_9c and MFB_20c

3. Results and discussion

3.1. *Evaluation of correction method*

Comparison of daily rainfall observed and corrected TRMM rainfall estimates showed that the daily corrected does not always result in improved accuracy, mainly in correlation (Table 2). Increasing of correlation is not always followed improvement of correction of TRMM rainfall estimates. There are only 2 methods better than original TRMM rainfall estimates, there are conditional merging (CM) and local bias with 20 classes. From mean, maximum and minimum correlation, all local bias and its modified have better correlation than mean field bias and its modified.

Base on RMSE and MAE show that CM and modified local bias are better than original TRMM rainfall estimates and other methods. Because of the value of mean of RMSE and MAE, CM and modified local bias smaller than TRMM. Although CM and modified local bias are better on average of RMSE, but maximum value of RMSE and MAE are bigger than TRMM. Comparison both of the best models, although CM is better in the mean of RMSE but classified LB results has stable errors with smaller maximum RMSE and MAE than CM. Also, modified LB has better MAE than other methods includes CM.

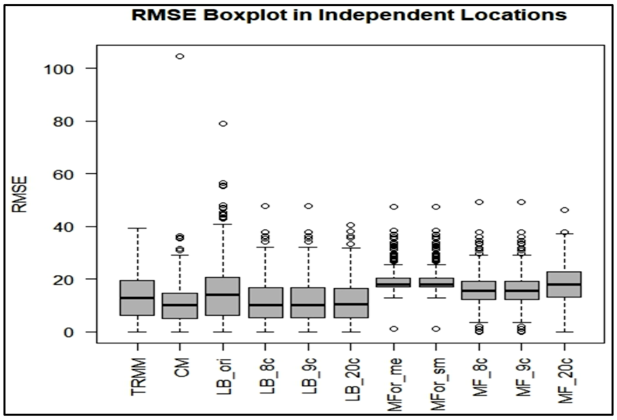

Fig. 3. Root mean square error (RMSE) in bloxplot of TRMM rainfall estimates, conditional merging (CM), original local bias (LB_ori), modified local bias with 8, 9 and 20 classes respectively LB_8c, LB_9c and LB_20c, mean field bias with mean (MFor_me), mean field bias with summation (MFor_sum) and modified mean field bias with 8, 9 and 20 classes respectively MFB_8c, MFB_9c and MFB_20c

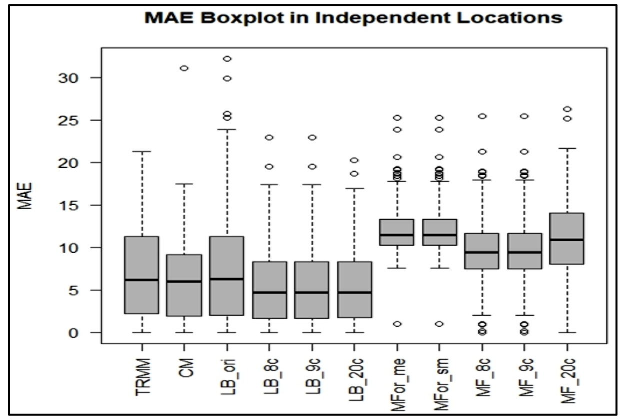

Fig. 4. Mean absolute error (MAE) in bloxplot of TRMM rainfall estimates, conditional merging (CM), original local bias (LB_ori), modified local bias with 8, 9 and 20 classes respectively LB_8c, LB_9c and LB_20c, mean field bias with mean (MFor_me), mean field bias with summation (MFor_sum) and modified mean field bias with 8, 9 and 20 classes respectively MFB_8c, MFB_9c and MFB_20c

Figs. (2-4) show the distribution of boxplot distribution of RMSE, MAE and correlation of TRMM rainfall estimates and its correction. The MFB and its modified have lower RMSE and MAE than TRMM rainfall estimates, while local bias and modified local bias almost equal to TRMM prediction. Comparing other correction methods, CM is the best in correlation. On the contrary, boxplot distribution of local bias and modified local bias are almost similar to original TRMM rainfall estimates. Among local bias methods, modified local bias with 20 classes has slightly better than others, because the third quartile is higher than others.

Modified local bias can improve in RMSE and MAE. Comparing with the original local bias [Figs. (3&4)], these modified methods can reduce error less than TRMM rainfall estimates, mainly in MAE. The distribution of MAE of all modified local bias is slightly narrower than other methods. While, CM has smaller RMSE and slightly narrower than modifying local bias. Also, mean field bias and modified mean field bias have worse, both in RMSE and MAE than CM, local bias and modified local bias. Among correction methods, original MFB has the biggest in RMSE and MAE. Although its modified MFB still can improve but not better than LB and CM.

Among correction methods, conditional merging (CM) is frequently said the best methods (Sik *et al*., 2007; Goudenhoofdt and Delobbe, 2009). But in this work, based on statistical performance modified local bias with 20 classes slightly better than CM. Although classified ratio of the local bias must be done carefully since not all classified of the ratio results better than original TRMM rainfall estimates. The both of these methods are better than MFB and its modified. Comparison with other the tropical region such as Thailand that states MFB is the best correction method (Mahavik, 2017), in around Makassar Strait, original MFB result the worst among the methods. Although added classes of ratio make better in accuracy than original, but it is still worse than original TRMM rainfall estimates. While, adding classing LB, it can be significant to reduce errors. Value of RMSE and MAE of modified LB is relatively smaller than others. Although this modified also can reduce correlation, but it is not very significant. Addition, modified CM by using IDW interpolation makes possible to avoid fail in semivariogram modelling and results close performance modified LB.

3.2. *Corrected bias related to MJO phase*

The MJO early develops over the Indian Ocean, then moves to eastward over the maritime continent (MC) and finally over the western Pacific (Wheeler and Hendon, 2004; Birch *et al*., 2016). Impact of MJO to the rainfall varies respect to location and time (Seetharam, 2008; Zhang, 2013). While, increasing rainfall in Indonesian region related to MJO phase 3 and 6. Particularly in surrounding of the Makassar Strait, rainfall raises when MJO in phase 4 and 5. The magnitude of MAE of the best modified corrected bias of TRMM rainfall estimates can be seen in Fig. 5.

Grouping MAE based on MJO phase shows that phase 1 and 5 of MJO results the smallest error. The first

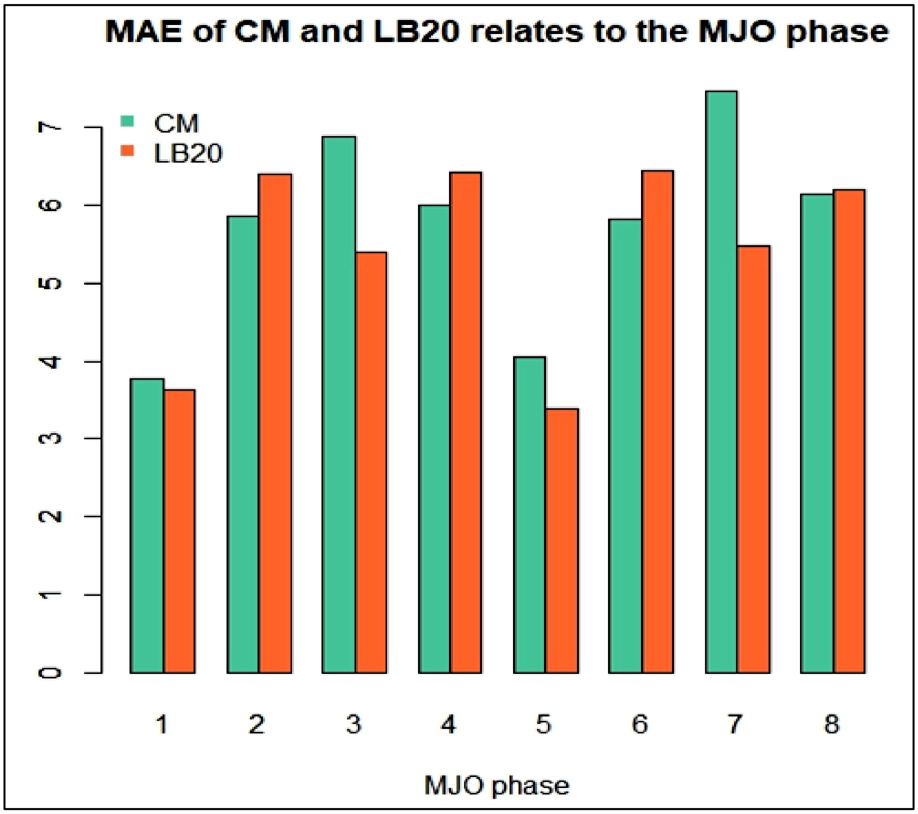

Fig. 5. MAE of two the best corrected bias of TRMM rainfall estimates, conditional merging (CM) and modified local bias 20 classes (LB20) respect to MJO phase

phase of MJO is phase where MJO is not active in Indonesia, so that rare event happens in Indonesian region. While the fifth phase of MJO make a lot of rainfall in IMC region include the Makassar Strait. The value of MAE and RMSE in TRMM rainfall estimates strong relate to rainfall intensity, mostly rainfall persistency (Giarno *et al*., 2018). This work apparently support this assumption, where the first phase and fifth of MJO relates the dry and moist of MJO impact in the Makassar Strait.

4. Conclusions

Performance of modified mean field bias (MFB) and local bias (LB) can be increased by classified of the categorized correction factor, mainly in reducing root mean square error (RMSE) and mean absolute error (MAE). Although improvement of the correlation is rather difficult. Only conditional merging (CM) and modified LB with 20 classes can increase the value of the correlation. Moreover, choosing the class of a ratio also determine a goodness of the correction. LB and CM are better methods than MFB. Moreover, modified LB can be considered as the best correction method because of the stabilization of MAE, while CM is the best method to reduce RMSE. Adding, avoiding error in a correction factor by adding 1 mm is needed to rainfall in each station.

Deviation of correction methods relates to the persistence of rainfall or not of this region. Corrected bias can increase perform of TRMM rainfall estimates in the driest and the wettest MJO impact. It may be appropriate in a future study to variation pattern of the ratio, appropriate method in IMC region and verify in the long term. Also, its relation to the impact respect to primary rainfall driven in this region.

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