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Comparison Accuracy of CHIRPS, GSMaP V7, and GSMaP V8 Satellite Rainfall Estimation in Kalimantan

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ABSTRACT

The application of satellite product rainfall estimates (SPREs) is growing in hydrometeorology due to limited rainfall measurement. This study aims to compare the accuracy of three SPRE, namely Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), Global Satellite Mapping of Precipitation (GSMaP) Moving Vector with Kalman Filtering (GSMaP-MVK), and near-real-time (GSMaP-NRT) versions 7 and 8, against daily and monthly rainfall measurements from eighteen gauges in Kalimantan from December 2021 to May 2023. Continuous validation includes root mean square error (RMSE), relative bias (RB), and correlation coefficient (CC), and categorical validation consists of a probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) were used to assess the accuracy of SPREs. The results showed that GSMaP-MVK version 8 has the highest accuracy on a daily scale with an RMSE value of 14.31 mm/day, while the CHIRPS has the highest accuracy on a monthly scale with an RMSE of 81 mm/month. GSMaP version 8 is better than GSMaP version 7, with a difference in RMSE, CC, and RB at 14.2%, 9.7%, and 84%. Categorical validation showed that GSMaP version 8 was 2.13%, higher in POD, 3.95% in CSI, and 10.2% in FAR compared to GSMaP version 7.

1. INTRODUCTION

Rainfall is the primary controller in the hydrologic cycle and is an essential variable in water resource management, flood, drought monitoring, and early warning systems (Sheffield *et al*., 2018). Rainfall intensity can be measured using rain gauges, radar, and satellite sensors. However, the rain gauge network is uneven due to terrain conditions and cost (Shi *et al*., 2021), causing difficulty in obtaining rainfall data with high spatial-temporal resolution (Ning *et al*., 2017) and limiting its use in hydrometeorology.

Satellite product rainfall estimates (SPREs) can be an alternative to limited rainfall measurement data because they have high spatial and temporal resolution (Roy & Banu, 2021). SPREs can be classified into three types based on their source: i) passive microwave data from the low-orbit satellites: ii) infrared radiometer data from geostationary satellite observations (Yeh *et al*., 2020); and iii) a combination of two to generate global rainfall estimates with high spatial-temporal resolution (Derin *et al*., 2019). SPREs which are a combination of passive microwave and infrared, include the Tropical Rainfall Measuring Mission (TRMM) - Multi-satellite Precipitation Analysis (TMPA, 0.25°/3 hour), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network (PERSIANN, 0.25°/1 hour), Climate Prediction Center Morphing Method (CMORPH, 0.25°/30 minutes), and Global Satellite Mapping of Precipitation (GSMaP, 0.25°/1 hour).

Climate Hazards Group Infrared Precipitation with Station (CHIRPS) data is a quasi-global rainfall estimation covering 50°N-50°S with a spatial resolution of 0.5° and available in temporal resolution daily, 5-day, 10-day, and monthly (Funk *et al*., 2015), from 1981 – present. CHIRPS is a combination of satellite product data and rain gauge data. It consists of 3 data components: Climate Hazards Group Infrared Precipitation (CHIRP), Climate Hazards Group Precipitation Climatology (CHPClim), and procedures for blended rainfall combinations.

Global Satellite Mapping of Precipitation (GSMaP) is a global rainfall estimation covering a 60°N-60°S area with a spatial resolution of 0.1° × 0.1° and 1-hour temporal resolution developed by the Japan Science and Technology Agency in 2002 (Roy & Banu, 2021). GSMaP is a multi-satellite product rainfall estimation that combines passive microwave (PMW) and infrared radiometers (IR). Rainfall intensity is estimated from PMW brightness temperature, then corrected using IR data with the Kalman Filter technique to obtain hourly global rainfall estimates with a spatial resolution of 0.1° (Satgé *et al*., 2018). GSMaP rainfall estimates include four types, namely, standard products, near-real-time products, and reanalysis results. GSMaP Moving Vector with Kalman Filtering (GSMaP-MVK) is a standard product with a latency of 3 days, while GSMaP near-real-time (GSMaP-NRT) is a near real-time product with a latency of 4 hours (Kubota *et al*., 2020). GSMaP-MVK and GSMaP-NRT combine passive microwave and infrared data on the Kalman Filter model. The main difference between GSMaP products is that the GSMaP-NRT algorithm is based on the standard GSMaP-MVK algorithm, but the process is simplified to produce data with low latency (Kubota *et al*., 2020). GSMaP-NRT only uses forward propagation in the moving vector algorithm, while GSMaP-MVK uses forward and backward propagation algorithms (Li *et al*., 2021; Lu & Yong, 2020; Wang *et al*., 2021). The latest GSMaP product is GSMaP version 8 (GSMaP v8), released in December 2021. GSMaP v8 improves GSMaP version 7 (GSMaP v7), released in January 2017 and available from March 2014 to the present. Several improvements in GSMaP version 8 are in PMW-IR and the gauge-adjustment algorithm. The improvements in the PMW-IR algorithm includes using the hail thickness method and an algorithm for orographic heavy rain (Ramadhan *et al*., 2023), and due to the histogram adjustment method (Kubota *et al*., 2020).

Kalimantan is the third-largest island in the world, covering an area of 743,330 km² with a topography of mountain ranges stretching from northeast to southwest (Supari *et al*., 2016). Rainfall intensity varies from 1,700 mm/year in the coastal areas (southern and eastern parts) to 4,100 mm/year in the central region. The annual rainfall pattern of Kalimantan is divided into two climatic zones: the monsoon in the south and the equatorial in the north and west. The monsoon zone has one peak rainfall in December-January-February (DJF) and months with low rainfall in June-July-August (JJA). The equatorial zone has two rainfall peaks, in October-November (ON) and March-May (MAM) (Aldrian & Susanto, 2003; Arini *et al*., 2015). The northwestern monsoon influences the monsoon zone in November-March (NDJFM) and the southeast monsoon in May-September (MJJAS). The equatorial zone is affected by the movement of rain clouds that follow the apparent motion of the sun around the equator, which causes an increase in rainfall intensity in March-April-May (MAM) and September-October-November (SON) (Arini *et al*., 2015).

The accuracy of SPREs is affected by several factors, namely the algorithm used, the nature of the sensor used, the condition of the earth's surface, and the type of rain (Gebregiorgis & Hossain, 2015). Several studies on GSMaP accuracy in Indonesia and Kalimantan include GSMaP-NRT v6 (Fatkhuroyan & TrinahWati, 2018), GSMaP-MVK v7 (Fatkhuroyan *et al*., 2018), and GSMaP v8 (Ramadhan *et al*., 2023). The GSMaP-MVK has the highest accuracy for all GSMaP v8 types of datasets, whereas, for GSMaP with low latency, the GSMaP-NRT v8 has the highest accuracy (Ramadhan *et al*., 2023). However, this research is still limited to verifying the accuracy of one version of GSMaP without comparing it with previous versions. The study also does not involve analysis bias decomposition. The analysis of bias decomposition can show the bias type, which is helpful as a reference for improving the algorithms of satellite product rainfall estimates. So, comparing the latest version of GSMaP with previous versions and analysis bias decomposition show the level of improvement of the new versions of GSMaP. A comparison of the accuracy of GSMaP with a higher spatial resolution SPRE, namely CHIRPS, is necessary for determining the type of satellite rainfall dataset used in water resources management.

The study objectives are to 1) compare the accuracy of the SPREs (CHIRPS, GSMaP-MVK version 7 and 8, and GSMaP-NRT version 7 and 8) over Kalimantan for the period December 2021 to May 2023 on a daily and monthly scale using continuous and categorical validation, 2) identify improvement in GSMaP version 8 over GSMaP version 7 using continuous and categorical validation, and 3) conduct component bias analysis.

2. MATERIALS AND METHODS

2.1. Study Area and Datasets

The study area is Borneo Island, located between 40° 24’N – 10° 10’S latitude and 108o 30’ – 119° 00’E longitude, as presented in Figure 1. The software used in the study includes Arc GIS 10.8, OpenGrADS 2.2, and SPSS 24. The materials include rainfall data from rain gauge observation stations from the Meteorology, Climatology, and Geophysical Agency (BMKG), CHIRPS, and GSMaP. A summary of the characteristics of daily rainfall from rain gauge observation is present in Table 1.

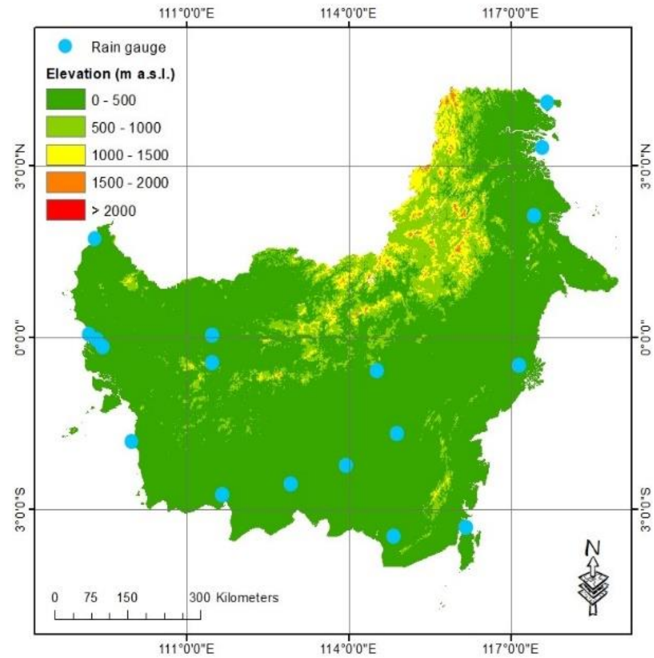

Figure 1. Study area and rain gauge network.

Table 1. Rainfall station data for the period December 2021 – May 2023.

No	Station	Geographic Extent (°)		Altitude (m asl)	Missing Data (%)	SNHT-test (p-value)	Maximum (mm/day)	Total Rainfall (mm)
		Longitude	Latitude					
1	Tjilik Riwut	113.95	-2.22	27	8.0	0.664	61.5	4222
2	Beringin	114.53	-0.56	42	9.1	0.363	77.3	4770
3	H. Asan	112.93	-2.55	3	21.2	0.343	77.6	4208
4	Iskandar	111.66	-2.73	22	16.1	0.711	63.8	3724
5	Sanggau	114.90	-1.67	37	13.9	0.710	67.5	4013
6	Mar. Pontianak	109.34	-0.03	4	19.6	0.071	61.9	3643
7	Mempawah	109.19	0.08	2	22.3	0.260	63.0	3216
8	Nangapinoh	111.47	-0.42	40	18.3	0.958	85.6	5644
9	Susilo	111.47	0.06	31	9.3	0.994	80.0	4154
10	Supadio	109.45	-0.14	3	16.1	0.605	64.0	3276
11	Paloh	109.30	1.74	15	7.7	0,087	72.7	3512
12	Rahadi Oesman	109.97	-1.80	9	13.2	0.033	82.0	5139
13	Banjar Baru	114.84	-3.46	55	21.9	0.352	66.7	3824
14	Gusti Syamsir	116.17	-3.30	2	22.9	0.118	57.8	2927
15	Kalimaru	117.43	2.15	13	25.0	0.834	65.8	3334
16	Temindung	117.16	-0.48	10	20.3	0.412	61.8	3483
17	Juwata	117.57	3.33	6	10.6	0.226	64.4	4590
18	Nunukan	117.67	4.13	8	14.8	0.321	63.0	2473

1. Daily rainfall data in the research area from December 2021 to May 2023 were obtained from Meteorology, Climatology, and Geophysical Agency (BMKG) rain gauge observation and downloaded on the website https://dataonline.bmkg.go.id.
2. Hourly data GSMaP-NRT and GSMaP-MVK version 7 and 8 in .dat format downloaded on the website ftp://hokusai.eorc.jaxa.jp.
3. CHIRPS daily rainfall data in NetCDF format obtained from the website https://data.chc.ucsb.edu/products.

2.2. Pre-processing data

The pre-processing of daily rainfall data from rain gauge (RG) measurements by BMKG includes selecting rainfall stations. Rainfall stations in Kalimantan were determined using a 25% percentage missing data threshold (Mamenun *et al*., 2014), with missing data more than 25% excluded from the validation analysis. The results of selecting rainfall stations from 23 stations showed that five stations had more than 25% missing data, so the validation only used 18 rainfall stations in Kalimantan (Figure 1). The daily rainfalls were tested for homogeneity using the Standard Normal Homogeneity Test (SNHT) at 5% level of significance. The homogeneity test result (Table 1.) showed that one station (Rahadi Oesman) was rejected the null hypothesis at 5% level of significance. Outlier data is also not included in the validation analysis. Data outliers were determined using the standard deviation method (Budiyono & Faisol, 2021). The pre-processing data of GSMaP v7 and v8 was to extract data in .dat format, corresponding to rainfall station coordinates, using OpenGrADS software to obtain hourly rainfall data in the Universal Time Coordinate (UTC) time standard. The hourly rainfall GSMaP accumulated to obtain daily rainfall based on the UTC zone adjusted to the local time zone. Rainfall accumulation starts at 00.00 UTC for rain stations in the WIB zone and at 01.00 UTC for rain stations in the WITA zone. The pre-processing of CHIRPS daily rainfall is extracting data in NetCDF format using Arc GIS software with the point-to-pixel method.

2.3. Continuous validation

The accuracy of SPREs assessed by comparing estimated rainfall with measurement rainfall at the 18 rainfall stations on daily and monthly scales. Because the GSMaP v8 products only released in December 2021, the accuracy calculated for December 2021 to May 2023. The continuous statistic used to assess the accuracy of rainfall estimates from satellite data is the correlation coefficient (CC), shown in Equation 1, root mean square error (RMSE) in Equation 2, and relative bias (RB) in Equation 3 (Darand & Siavashi, 2021; Lei *et al*., 2023; Lu & Yong, 2018; Ramadhan *et al*., 2022).

$$CC = \frac{\left[\sum_{i=1}^{n}(S_i - \bar{S}) * (G_i - \bar{G})\right]^2}{\sum_{i=1}^{n}(S_i - \bar{S})^2 * \sum_{i=1}^{n}(G_i - \bar{G})^2} \tag{1}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}(S_i - G_i)^2} \tag{2}$$

$$RB = \frac{\sum_{i=1}^{n}(S_i - G_i)}{\sum_{i=1}^{n}(G_i)} * 100\% \tag{3}$$

3. Categorical validation

The performance of CHIRPS, GSMaP v7, and GSMaP v8 was validated using a categorical validation based on a contingency table (Table 2). The categorical metrics used include the probability of detection (POD) in Equation 4, the false alarm ratio (FAR) in Equation 5, and the critical success index (CSI) in Equation 6.

Table 2. Categorical value

		Observed rainfall (mm/day)	
		rainfall > 0.5	rainfall = 0.5
Satellite estimated (mm/day)	rainfall > 0.5	hits (a)	false (b)
	rainfall = 0.5	misses (c)	correct no rain (d)

$$POD = \frac{a}{a+c} \tag{4}$$

$$FAR = \frac{b}{a+b} \tag{5}$$

$$CSI = \frac{a}{a+b+c} \tag{6}$$

In the equation above, the hit value (a) is that satellite data has successfully detected rain, false (b) the satellite data has failed to detect no rain, miss (c) the satellite data has failed to detect rain, while correct no rain (d) satellite data capable of detecting the occurrence of non-occurrence rain.

POD is the estimated percentage of rain events that occurred, ranging from 0 to 1, whereas FAR is the fraction of rain events that did not occurred, ranging from 0 to 1 (Mughal *et al*., 2020; Xiao *et al*., 2020). The rainfall threshold of 0.5 mm/day used to determine whether it rained or not (Budiyono & Faisol, 2021; Helda & Ramadhani, 2023; Prakash *et al*., 2016). CSI is an index of the overall ability of satellite data to capture rain events. POD and CSI values close to 1 and FAR values close to 0 indicate good performance satellite data.

2.4. Analysis of Decomposition Bias

The threshold value between rain and no rain of 0 mm/day (Gumindoga *et al*., 2019; Lekula *et al*., 2018) used to analysis bias decomposition of rainfall satellite estimated. The bias consists of hit bias (HB) in equation 7, miss bias (MB) in equation 8, and false bias (FB) in equation 9. Hit bias can be positive or negative, and a negative value indicates underestimation and vice versa for a positive value. The MB value is always negative, while the FB value is always positive.

$$HB = \frac{\sum_{i=1}^{n}(S_i - G_i)}{\sum_{i=1}^{n}(G_i)} * 100, (S_i > 0 \; and \; G_i > 0) \tag{7}$$

$$MB = \frac{-\sum_{i=1}^{n}(S_i)}{\sum_{i=1}^{n}(G_i)} * 100, (S_i = 0 \; and \; G_i > 0) \tag{8}$$

$$FB = \frac{\sum_{i=1}^{n}(S_i)}{\sum_{i=1}^{n}(G_i)} * 100, (S_i > 0 \; and \; G_i = 0) \tag{9}$$

3. RESULTS AND DISCUSSION

3.1. Characteristics of Daily Rainfall

The accumulation of average daily rainfall in Kalimantan and satellite estimates from December to May 2023 shown in Figure 2. It showed that GSMaP-NRT v8 was a good estimate with accumulated rainfall measurements (marked with a coinciding line). The GSMaP-MVK v7 rainfall estimate shows the lowest estimation accuracy and tends to overestimate. Meanwhile, the CHIRPS is overestimated but slightly better than the GSMaP-MVK v7. Figure 2 also indicates that GSMaP v7 tends to overestimate, while GSMaP v8 tends to underestimate.

Figure 3 shows a boxplot of average measurement and satellite estimation of daily rainfall from December 2021 to May 2023. Figure 3 shows that the median of the GSMaP-NRT v8 is 6.8 mm, and GSMaP-MVK v7 is 8.5 mm, close to the median rainfall measurement of 7.6 mm. The highest median was found in GSMaP-NRT v7 (9.4 mm), then CHIRPS (9.3 mm), and GSMaP-MVK v7 (8.5 mm). The median strengthens the conclusion in Figure 2 that the GSMaP-NRT v7, CHIRPS, and GSMaP-MVK v7 data are higher than the measurement.

The estimated rainfall of GSMaP-NRT v8 was an average of 8.5 mm, close to the measurement average (8.4 mm). However, it was a higher distribution of 77% compared to the measurement, with a distribution of 64.1%. In contrast, CHIRPS distribution data was the lowest at 52.3%. The highest average value was found in the GSMaP-NRT v7 at 11.1 mm, followed by GSMaP-MVK v7 at 10.2 mm. Meanwhile, the average rainfall for GSMaP-MVK v8 is the lowest among the other SPREs at 7.4 mm.

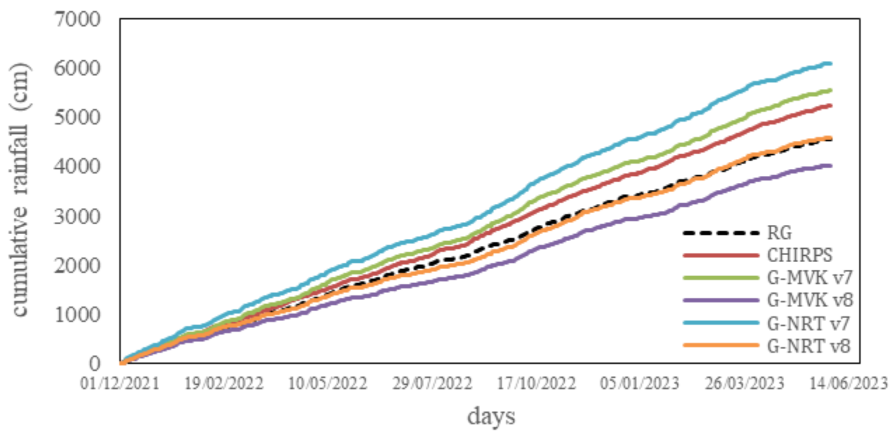

Figure 2. Accumulated average daily rainfall measurements and satellite estimates.

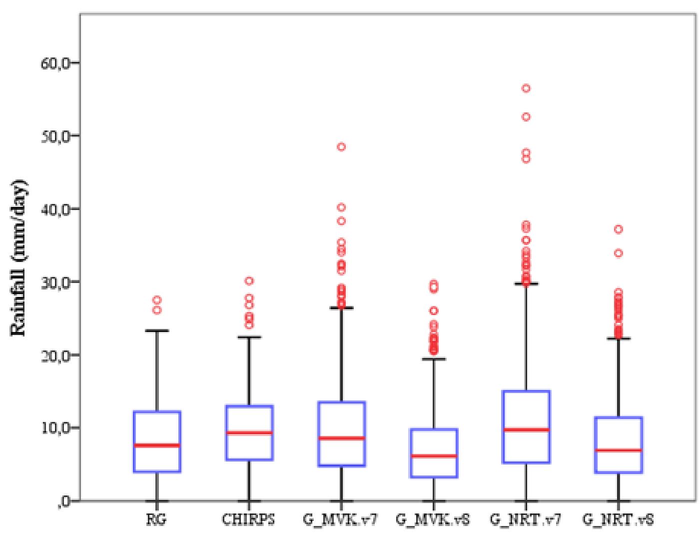

Figure 3. Boxplot of average daily rainfall (mm) measurements and estimated satellite in Kalimantan.

3.2. Daily Rainfall Validation

Figure 4 shows that the estimated GSMaP-NRT v8 is close to the measurement with a CC of 0.45, while CHIRPS has the lowest CC at 0.13. The CC value is also lower than the CC value in West Kalimantan, which is 0.25 (Suryanto *et al*., 2023). The CC value of the GSMaP-MVK v7 data is lower than the average CC value from 2014 to 2017, which is 0.49 (Fatkhuroyan *et al*., 2018). The GSMaP-NRT v8 CC value is lower than the average CC value in Indonesia, which is 0.41, while the GSMaP-MVK v8 is 0.45 (Ramadhan *et al*., 2023). The percentage change in the validation parameter value showed the improvement in GSMaP. The GSMaP-MVK CC value increased by 8.9% from version 7 to version 8, while GSMaP-NRT experienced a higher increase of 10.3%.

The lowest RMSE in GSMaP-MVK v8 was 14.31 mm/day, while the highest was GSMaP-NRT v7 which was 19.35 mm/day. RMSE value GSMaP-MVK v7 obtained at 16.38 mm/day is higher when compared to the results obtained in the Kalimantan region during 2014–2017, which was 16.32 mm/day (Fatkhuroyan *et al*., 2018). Meanwhile, the RMSE value of the CHIRPS was 15.76 mm/day, lower than the RMSE value in West Kalimantan of 19.82 mm/day. The RMSE of GSMaP-MVK version 8 was smaller than version 7 by 15.10%, while in GSMaP-NRT it was 13.5%. The decrease in RMSE indicates that improving the GSMaP algorithm in version 8 can reduce errors in estimating daily rainfall. Figure 4 shows daily average rainfall estimated by satellite with rainfall measurements.

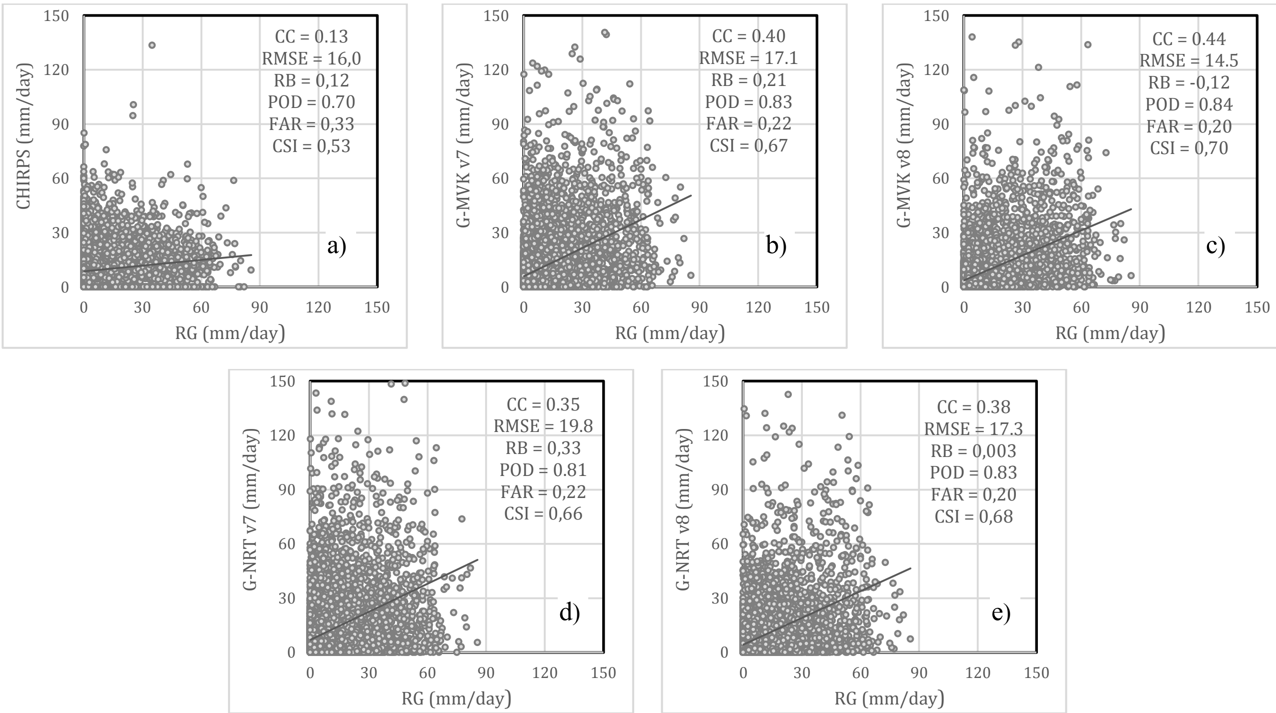

Figure 4. Scatter diagrams of daily average rainfall estimated by satellite with rainfall measurements in Kalimantan, a) CHIRPS, b) GSMaP-MVK v7, c) GSMaP-MVK v8, d) GSMaP-NRT v7, and e) GSMaP-NRT v8.

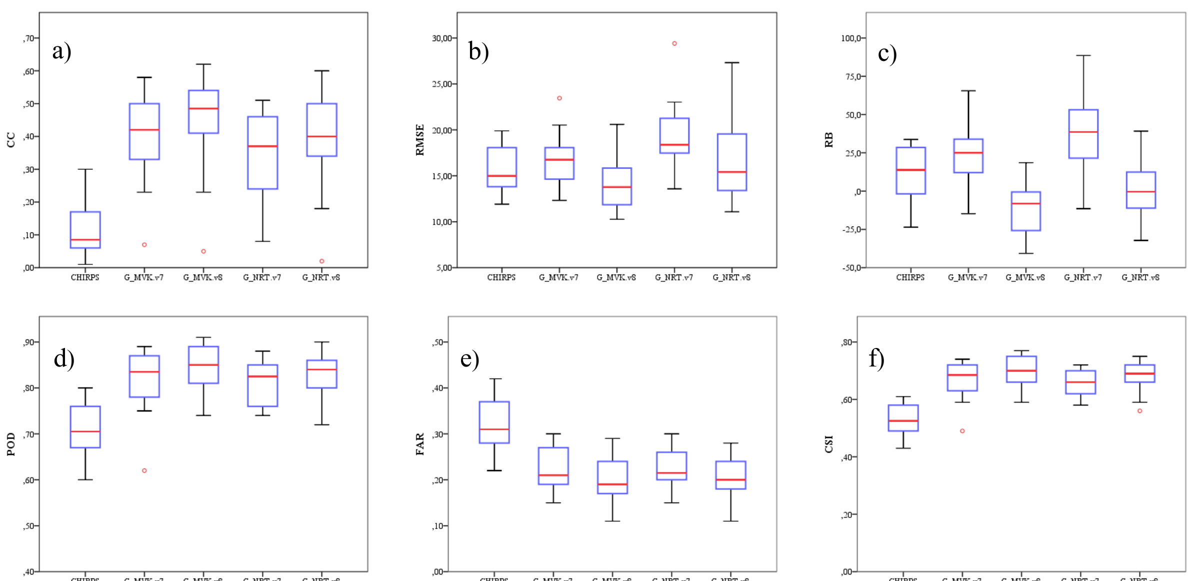

Figure 5. Boxplot diagram of daily rainfall accuracy in Kalimantan: a) correlation coefficient (CC), b) root mean square error RMSE), c) relative bias (RB), d) probability of detection (POD), e) false alarm ratio (FAR), g) critical success index (CSI).

The correlation coefficient (CC) value indicates that GSMaP v8 is higher than GSMaP v7. Unlike the GSMaP, the CC of CHIRPS shows no relationship between the measurement and a CC value closest to 0 (Figure 5a). The coefficient correlation of GSMaP-MVK is in the moderate category (0.40 – 0.59) and higher than the CC of GSMaP-

NRT in the weak category (0.20 – 0.39). The highest RMSE was found in GSMaP-NRT v7 (Figure 4b), while the lowest was in GSMaP-MVK v8, with 14.31 mm/day. Meanwhile, the RMSE GSMaP-NRT value of 18.04 mm/day is still higher than CHIRPS, with an average of 15.76 mm/day.

Figure 4 shows that all SPREs have an overestimated estimation with positive RB, except GSMaP-MVK v8 (-10.8%). The overestimation of CHIRPS caused by the absence of the surface altitude and the uncounted amount of rain that evaporates in the algorithm used (Rahmawati *et al*., 2021). The highest relative bias (RB) was found in GSMaP-NRT v7, and the lowest is in GSMaP-MVK v8. Figure 4c shows that the RB value of CHIRPS is better than the RB value of GSMaP-MVK v7 and GSMaP-NRT v7.

The probability of detection (POD) is an indicator of the success of estimating rain events that occur. In Figure 5d, the POD value for GSMaP data is close to 1 with an average of 0.83, while the POD for CHIRPS data is significantly lower (0.70). The false alarm ratio (FAR) and critical success index (CSI) have almost a similar pattern, the GSMaP data is not much different, while the CHIRPS has the highest FAR value and the lowest CSI.

3.3. Temporal Variability of Accuracy SPREs

Figure 6 shows the average daily rainfall value of measurement, satellite products, and validation parameters. The average daily rainfall measurement has three peak rainfall events in March, June, and October. Figure 6a shows that the rainfall pattern was similar to the semi-monsoon (equatorial) pattern. The average daily rainfall estimated by the

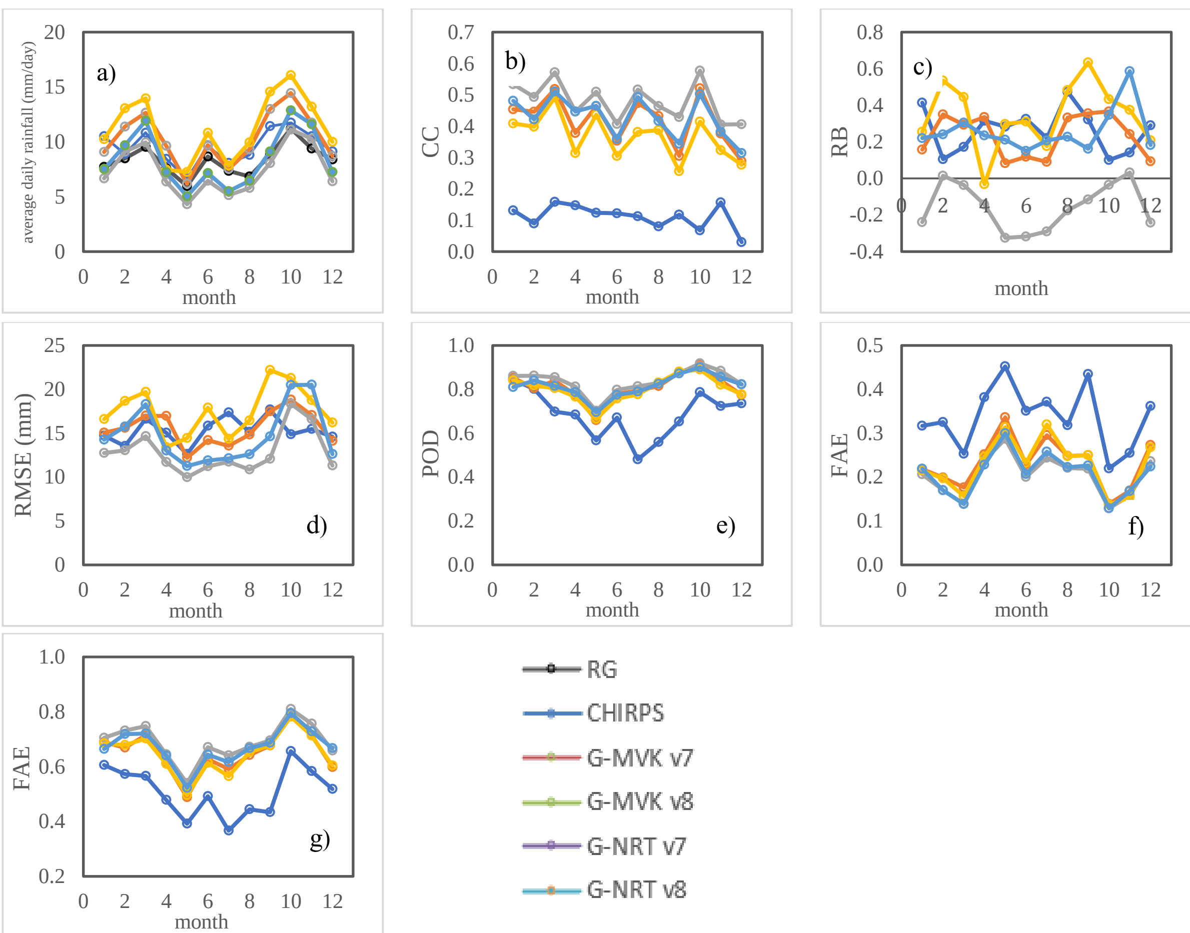

Figure 6. Temporal distribution of average daily rainfall and validation parameters: a) daily rainfall, b) coefficient correlation (CC), c) relative bias (RB), d) root mean square error (RMSE), e) probability of detection (POD), f) false alarm ratio (FAR), g) critical success index (CSI).

satellite shows an overestimate, except for GSMaP-MVK v8 and GSMaP-NRT v8; the overestimate only occurs in February-March and October-November. Overestimate the highest estimated rainfall from satellite data at the two peaks of rain, February and September-October, on GSMaP-MVK v7 and GSMaP-NRT v8.

The RMSE has a similar pattern to the average rainfall (Figure 6d). The satellite estimation produces a high error at high rainfall intensity, consistent with previous studies' results (López-Bermeo *et al*., 2022; Nadeem *et al*., 2022). The FAR value in Figure 6f has a clear pattern, which is the opposite of the rainfall pattern (Figure 6a). The FAR value tends to be low at high rainfall intensities and vice versa. Based on Figure 6b it is known that the parameter correlation coefficients (CC), RB, and CSI did not have a consistent pattern.

3.4. Spatial Pattern of Accuracy SPREs

Figure 7 shows that a strong and moderate linear relationship is dominant in the southern part of Kalimantan, and the northern part is weak. The very weak CHIRPS correlation is spread evenly in Kalimantan. GSMaP-MVK and GSMaP-NRT show increased CC from version 7 to 8 from southern to northern Kalimantan.

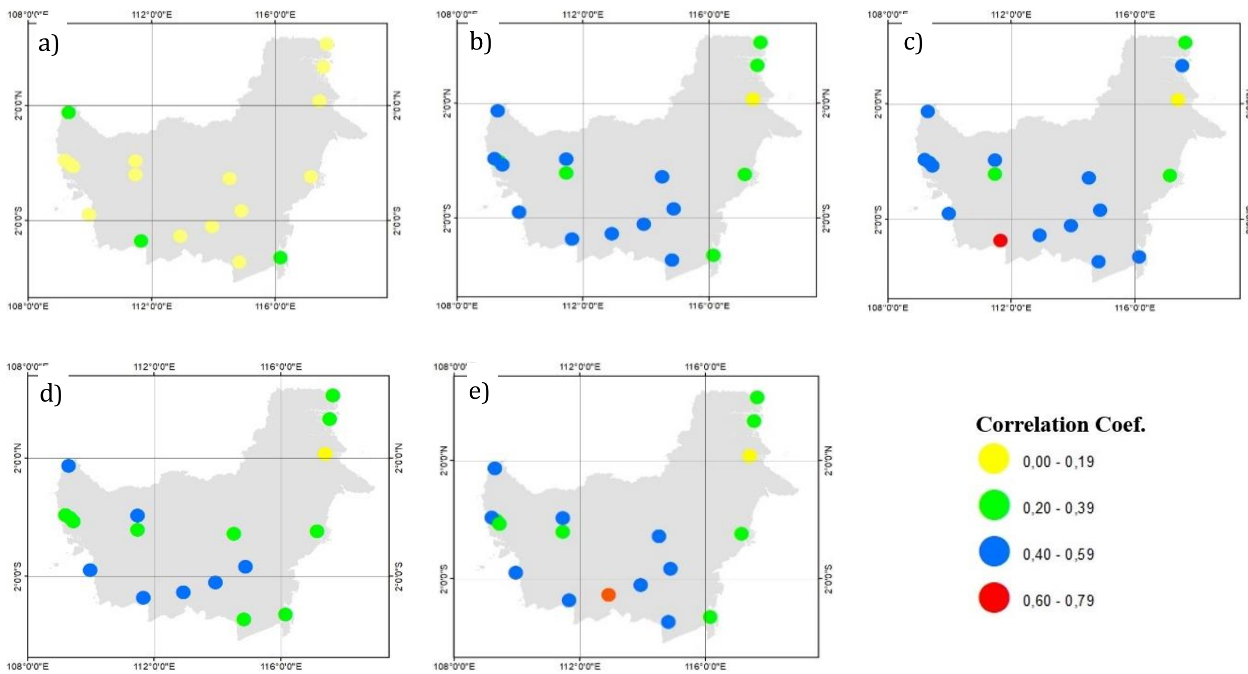

Figure 7. Distribution of Correlation Coefficient: a) CHIRPS, b) GSMaP-MVK v7, c) GSMaP-MVK v8, d) GSMaP-NRT v7, e) GSMaP-NRT v8.

Figure 8 shows the spatial distribution of RMSE satellite products at eighteen stations. RMSE is divided into five classes to interpret spatial distribution. The CHIRPS RMSE is significantly lower but still higher when compared to GSMaP-MVK v8 and is almost evenly distributed across all stations (Figure 8a). Meanwhile, RMSE GSMaP-NRT has a higher value than CHIRPS and GSMaP-MVK.

Figure 8 also shows that the highest RMSE of all satellite estimations tends to be in central Kalimantan. This is because convective rainfall dominates central Kalimantan during the inter-monsoon months (Sa *et al*., 2021), and convective rain is difficult to estimate by satellite sensors (Lu & Yong, 2020). RMSE in the northern part tends to be higher than in southern Kalimantan. The average total rainfall from December 2021 to May 2023 in the north, central, and western part of Kalimantan is 3097 mm, 4427 mm, and 3782 mm, respectively. This concludes that the RMSE value is higher in the station with high rainfall intensity, consistent with previous studies' results (Nepal *et al*., 2021).

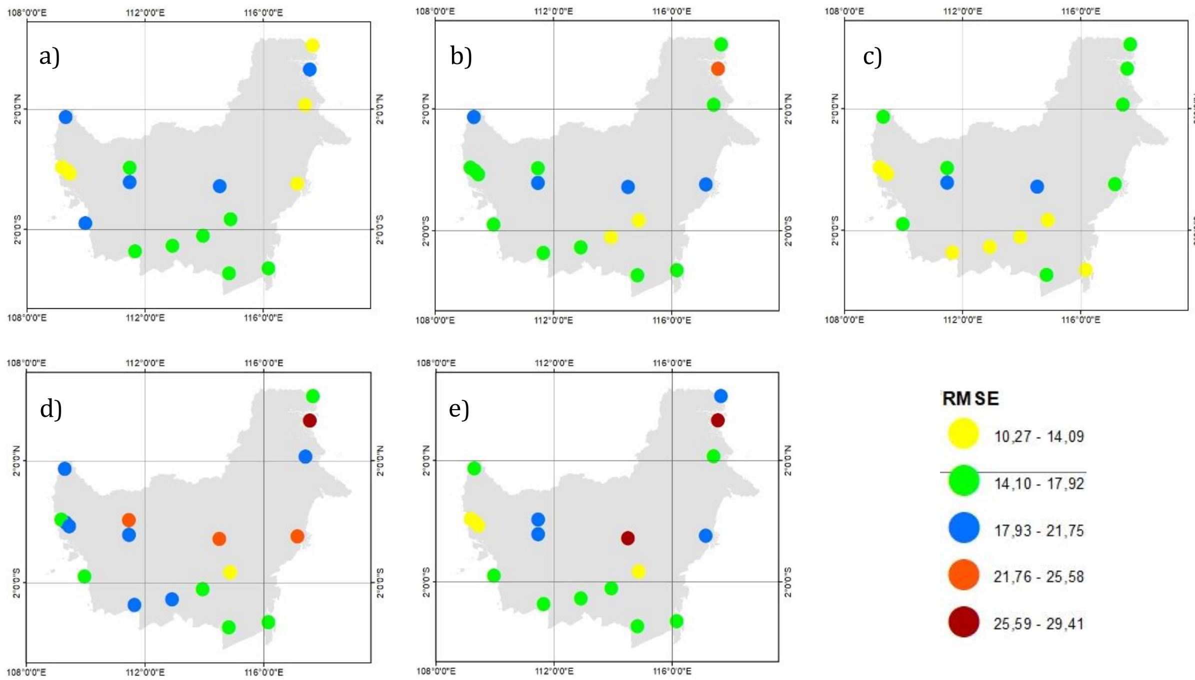

Figure 8. Distribution of RMSE: a) CHIRPS, b) GSMaP-MVK v7, c) GSMaP-MVK v8, d) GSMaP-NRT v7, e) GSMaP-NRT v8.

3.5. Bias Decomposition

Figure 9 shows the distribution of the bias components, which are hit bias (HB), miss bias (MB), false bias (FB), and total bias (TB). The bias of GSMaP-NRT v8 (Figure 9a) is lower than that of GSMaP-MVK v7 (Figure 9c) and CHIRPS (Figure 9a). The average total bias (TB) of the five SPREs, CHIRPS, GSMaP-MVK v7, GSMaP-MVK v8, GSMaP-NRT v7, and GSMaP-NRT v8 were 12.2%, 0.23%, -10.8%, 36%, and 1.3%, respectively. This shows that only GSMaP-MVK v8 produced an underestimate, while the other SPREs overestimated. In computing the total bias, FB and MB cancel each other out because the average FB and MB of the five SPREs are the same, i.e., -10.6% and 10.6%, respectively, so it concludes that the estimation satellites are underestimate or overestimate, as determined by the hit bias component.

Based on the MB value, the ability of CHIRPS to detect rainy days was the lowest (-0.27). It is because of rainfall estimates using information from infrared sensors on low-altitude clouds that tends to have high cloud-top temperatures (Ocampo-Marulanda *et al*., 2022). GSMaP-MVK v8 had the highest ability to detect rainy days (-0.43), followed by GSMaP-MVK v7 (-0.54), GSMaP-NRT v8 (-0.67), and GSMaP-NRT v7 (-0.90). The decrease in the value of the MB average showed the improvement of GSMaP v8 from v7. GSMaP-MVK v7 has an average MB of -5.4%, and GSMaP-MVK v8 is -4.3%. GSMaP-NRT v7 is -9.0%, and GSMaP-NRT v8 is -6.7%.

The FB bias component demonstrates how well satellite estimations can identify the absence of rain. GSMaP-MVK v7 has an average FB of 7.2%, and GSMaP-MVK v8 is 0.43%. GSMaP-NRT v7 has an average FB of 9.1%, while GSMaP-NRT v8 is 5.4%. Based on bias decomposition, it shows that the improvement of GSMaP-MVK and GSMaP-NRT from version 7 to version 8 is in the hit bias (HB), which reduces the total bias (TB).

3.6. Cumulative Distribution Function

The cumulative distribution function (CDF) of the average daily rainfall for December 2021 to May 2023 is shown in Figure 10. The measurement data has a probability of no-rain (0 - 0.5 mm) of 35.1%, rainfall intensity 0,5 – 2 mm/day to 20 – 50 mm/day is almost similar, 12.9% and 13.0%, 11.7%, 12.2% and 12.7%. Rainfall intensity > 50 mm/day has the lowest probability (2.3%). The probability of not raining occurrence of five SPREs is underestimated. The GSMaP-MVK v7 has the highest difference with measurement (31.9 %), while the best estimate is GSMaP-NRT v8

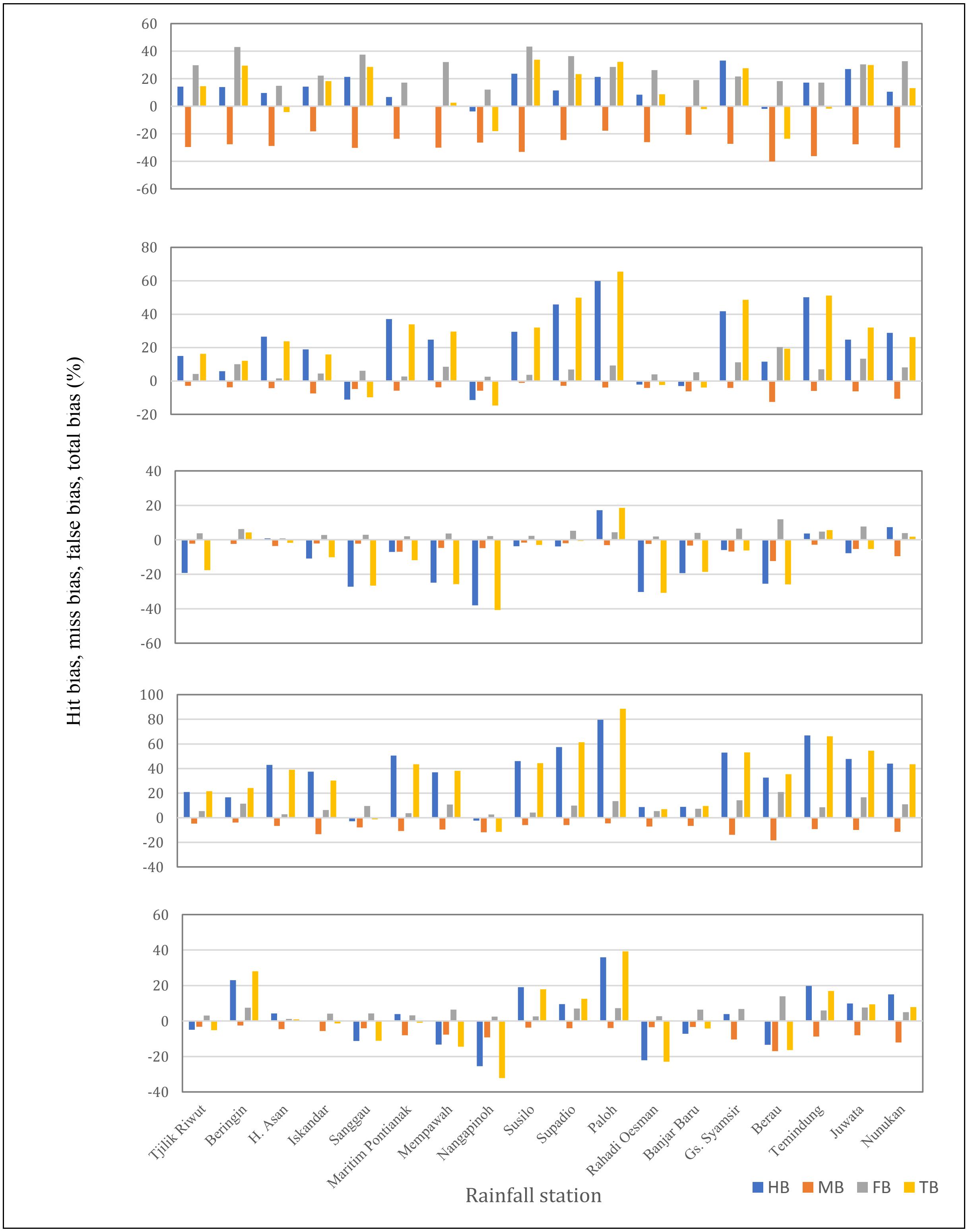

Figure 9. The composition of error: hit bias (HB), miss bias (MB), false bias (FB), and total bias (TB) of satellite product: a) CHIRPS, b) GSMaP-MVK v7, c) GSMaP-MVK v8, d) GSMaP-NRT v7, and e) GSMaP-NRT v8

(34.0%), and GSMaP-NRT v7 33.9%. This concludes that GSMaP-NRT version 7 and 8 has good performance to estimate very light to no rain (intensity < 0.5 mm/day). Based on the accuracy of the GSMaP-NRT v8 on the no rain, GSMaP-NRT v8 has potential use in meteorological drought analysis.

All five SPREs have overestimated at moderate rain events (5-20 mm/day). GSMaP version 8 underestimated at moderate rain (20-50 mm/day), whereas CHIRPS and GSMaP version 7 tended to overestimate. The underestimation of GSMaP v8 products might be due to the improvement in the PMW-IR algorithm.

Estimation on heavy to very heavy rain (≥ 50 mm/day), GSMaP-NRT v8 has the same probability with rain gauge measurement at 2.5% and GSMaP-MVK v8 with a probability of 1.9%. CHIRPS has the lowest estimate of 0.7%, while the GSMaP-MVK v7 and GSMaP-NRT v7 overestimate with probability of 3.4% and 4.4%. Based on the ability of GSMaP-NRT to estimate heavy to very heavy rain, the GSMaP-NRT v8 has potential for use in the analysis of flood early warning systems.

Figure 10 also shows that CHIRPS cannot estimate rainfall intensity of 0.5 – 2 mm/day and rainfall ≥ 50 mm/day, with probabilities of 0.2% and 0.7%. The estimation of satellite products is overestimate at rainfall intensities of 5 – 50 mm/day, except for GSMaP-MVK and GSMaP-NRT v8, which is underestimate.

3.7. Validation Monthly Rainfall

The accuracy of monthly rainfall in Figure 11 shows that all satellite estimate on a monthly time scale has a higher accuracy than a daily scale. The coefficient correlation was not much different between GSMaP-MVK and GSMaP-NRT; the lowest was in GSMaP-NRT v7 of 0.54 and GSMaP-MVK v8 was the highest for CC (0.62) with a moderate category correlation. The CHIRPS correlation coefficient was 0.67, and the category strongly relates to measurement.

The RMSE value of the CHIRPS was the lowest compared to GSMaP, which is 81.0 mm/month, while the lowest RMSE of GSMaP was in GSMaP-MVK v8 (87.8 mm/month). Based on the CC and RMSE values, CHIRPS is still better than GSMaP. The accuracy of CHIRPS on the monthly scale is better than a daily scale, both on CC and RMSE, consistent with previous studies results that accuracy increased as the temporal scale increased (Liu *et al*., 2020; Hsu *et al*., 2021; López-Bermeo *et al*., 2022). Based on the accuracy of the monthly rainfall estimate, CHIRPS has potentially used in meteorological drought analysis.

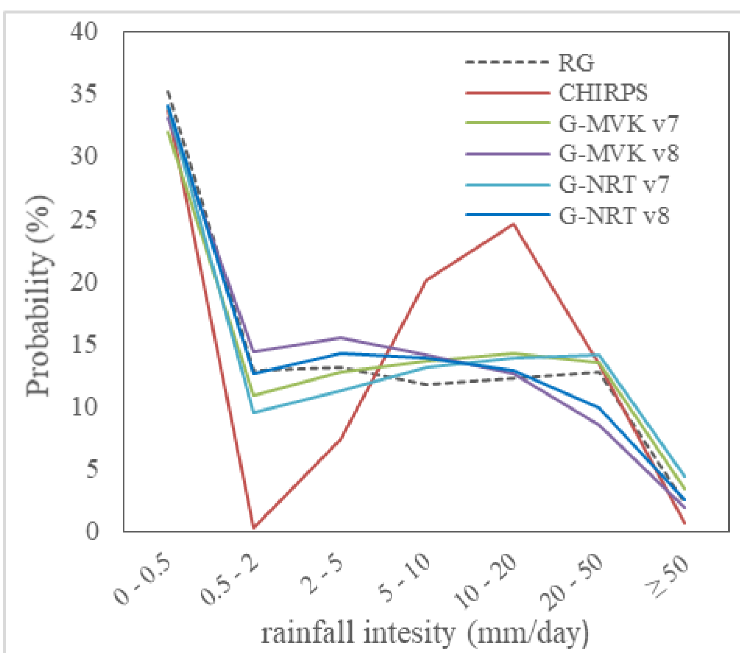

Figure 10. Cumulative distribution function (CDF) daily rainfall curve.

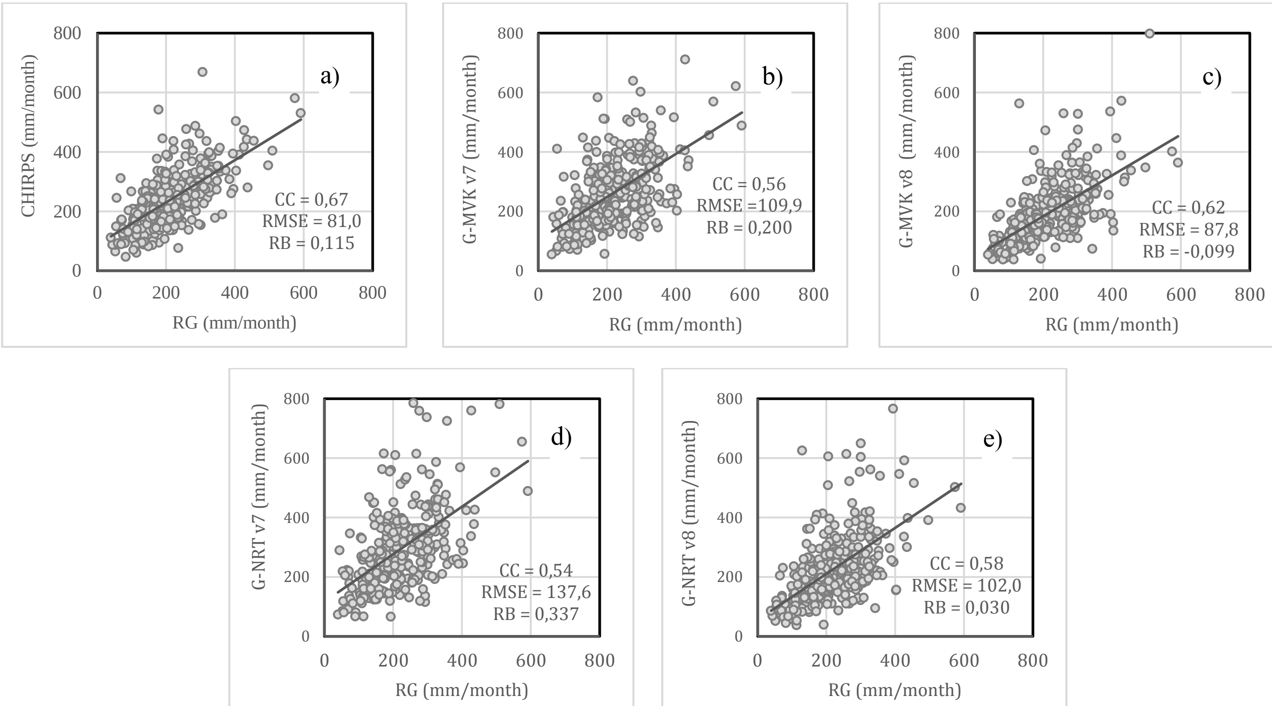

Figure 11. Scatter Diagram of monthly average rainfall estimated by satellite with rainfall measurement in Kalimantan: a) CHIRPS, b) GSMaP-MVK v7, c) GSMaP-MVK v8, d) GSMaP-NRT v7, and e) GSMaP-NRT v8.

4. CONCLUSIONS

A comparison of the accuracy of CHIRPS, GSMaP-MVK v7, GSMaP-MVK v8, GSMaP-NRT v7, and GSMaP-NRT v8 satellite products for daily rainfall for the period December 2021 to May 2023 at eighteen rain gauge stations in Kalimantan, was conducted using continuous and categorical validation. According to the continuous validation results of daily rainfall, the GSMaP-MVK v8 dataset has the highest accuracy, while categorical validation did not show a significant difference between GSMaP-MVK and GSMaP-NRT. The GSMaP has a dominant type of bias, hit bias, with an average value of 12.4%, while the CHIRPS data obtains a hit bias value of 13.0%. Improvements in GSMaP version 8 over version 7 are reduction of RMSE and relative bias (RB) by 14.2%, and 84% respectively. The GSMaP-NRT v8 data can estimating heavy to very heavy rain (50 mm/day), so it can used in the analysis of flood early warning systems. On a monthly temporal scale, CHIRPS data shows the highest accuracy compared to GSMaP-MVK and GSMaP-NRT, with an RSME value of 81.0 mm. Based on accuracy at a monthly temporal scale, CHIRPS can used for meteorological drought analysis instead of GSMaP-MVK and GSMaP-NRT.

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