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# Evaluating GSMaP for Effective Rainfall Estimation in the Bengawan Solo Hulu Watershed Region

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## ABSTRACT

Effective rainfall is an important parameter in water resource management because it represents the portion of rainfall that can be reliably utilized to meet crop water requirements. However, its estimation generally requires long-term rainfall observations, which are often limited in many regions. Satellite precipitation products offer an alternative rainfall data source, but their applicability for effective rainfall estimation remains insufficiently explored. This study evaluates the capability of Global Satellite Mapping of Precipitation (GSMaP) for estimating effective rainfall using observations from five rainfall stations around the Bengawan Solo Hulu Watershed Region, Indonesia, during 2015–2024. Daily GSMaP rainfall was compared with ground observations and used to calculate dependable rainfall with an 80% exceedance probability (R80) and effective rainfall for rice cultivation (Re). Performance was evaluated using CC, PBIAS, NSE, and MAE. The results showed that GSMaP had moderate performance for daily rainfall, with average CC and NSE values of 0.54 and 0.07. Performance improved at semi-monthly and monthly scales, with CC values of 0.83 and 0.87, respectively. GSMaP also represented the seasonal pattern of dependable rainfall. Effective rainfall estimated from GSMaP showed better agreement with observation-based estimates, with CC reaching 0.92 and NSE exceeding 0.66. These findings indicate that GSMaP has potential as an alternative data source for effective rainfall estimation in regions with limited rainfall observations.

**Keywords:** GSMaP, effective rainfall, R80, water resources

## INTRODUCTION

Rainfall is one of the most important hydrometeorological variables in water resource management. It is used for various purposes, including water availability analysis, irrigation planning, flood control, hydraulic structure design, and evaluation of regional hydrological conditions [1], [2]. These applications generally require long-term historical rainfall records to ensure reliable estimates. Several hydrological guidelines and studies recommend the use of daily rainfall records of more than 10 years [2], not less than 20 years [3], [4], or even 30 years [5] for water resource analyses.

However, continuous and spatially representative ground-based rainfall observations remain limited in many regions. Uneven distribution of rainfall stations, operational constraints, and missing data often make available rainfall records insufficient for hydrological and water resource applications [6], [7], [8]. These limitations have encouraged the use of alternative data sources that can provide rainfall information with broader spatial coverage and more consistent availability.

Advances in remote sensing technology have enabled rainfall estimation using satellite observations. Rainfall data generated from this technology are commonly referred to as satellite precipitation products (SPPs). Various SPPs have been developed and widely used, including the Tropical Rainfall Measuring Mission (TRMM), Integrated Multi-satellitE Retrievals for GPM (IMERG), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), and Global Satellite Mapping of Precipitation (GSMaP) [9], [10], [11]. Compared with ground-based rainfall observations, SPPs offer several advantages, including broad spatial coverage, high temporal resolution, and relatively uniform data availability in regions with limited rainfall observations [9], [10].

One of the widely used SPPs is GSMaP, which was developed by the Japan Aerospace Exploration Agency (JAXA). GSMaP provides rainfall data with a spatial resolution of approximately 0.1° × 0.1° and a temporal resolution of up to one hour [12], [13], [14]. Several studies have reported that GSMaP shows better accuracy than other SPPs in certain regions and evaluation settings [8], [10], [15]. In Indonesia, GSMaP has also been utilized by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) to support rainfall monitoring, weather forecasting, and climate-related disaster potential assessment [16].

Most previous studies have evaluated GSMaP based on its ability to represent actual rainfall at various temporal scales [11], [17], [18]. This approach is important for understanding the characteristics and accuracy of satellite rainfall data; however, it does not fully represent the usefulness of GSMaP in water resource applications. In practice, many water resource analyses do not directly use actual rainfall data, but instead rely on derived parameters obtained through statistical processing of long-term rainfall records.

One of these derived parameters is effective rainfall, which refers to the portion of rainfall that can be reliably utilized to meet crop water requirements [1]. Effective rainfall is widely used in irrigation planning, crop water requirement assessment, and agricultural water management, particularly for rice cultivation. It is generally calculated based on dependable rainfall obtained through statistical analysis of historical rainfall data. Because this process involves arranging rainfall data according to their probability of occurrence, random errors in daily rainfall data may become less dominant during the transformation process. Therefore, a satellite rainfall product with moderate accuracy in representing daily rainfall may still have the potential to produce reliable effective rainfall estimates.

Nevertheless, studies on the capability of GSMaP to estimate effective rainfall remain relatively limited compared with general satellite rainfall validation studies. Therefore, this study aims to evaluate the capability of GSMaP to estimate effective rainfall for rice cultivation using rainfall observations from five rainfall stations around the Bengawan Solo Hulu Watershed as a case study. The evaluation was conducted by comparing GSMaP performance against ground observations at various temporal scales, calculating dependable rainfall with an 80% exceedance probability (R80), and estimating effective rainfall derived from both data sources. The results are expected to provide insight into the potential of GSMaP as an alternative rainfall data source in regions with limited ground-based observations.

## RESEARCH METHODS

### Study Area and Data

This study used ground-based rainfall observations from five rainfall stations located around the Bengawan Solo Hulu Watershed, Central Java, namely Baturetno, Parangjoho, Nawangan, Colo, and Tawangmangu (Figure 1). The coordinates and elevations of each station are presented in Table 1. These stations were selected because they provide long-term rainfall records and represent varying topographic conditions, ranging from lowland to mountainous areas. This elevation variation is important for evaluating GSMaP performance under different topographic conditions.

Daily ground-based rainfall data were obtained from the Bengawan Solo River Basin Agency (BBWS Bengawan Solo) for the period from 1 January 2015 to 31 December 2024. Missing rainfall data were filled using the Inverse Distance Weighting (IDW) method, while data consistency was evaluated using Double Mass Curve (DMC) analysis.

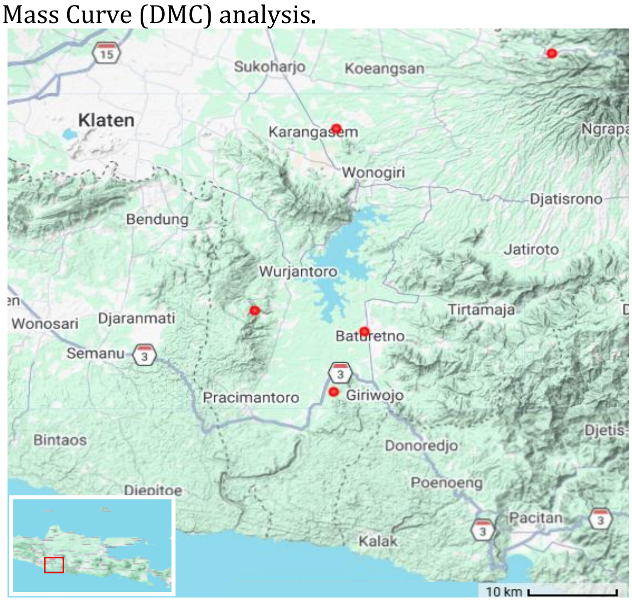


**Figure 1.** Location of rainfall stations in the Bengawan Solo Hulu Watershed

**Table 1.** Coordinates of rainfall stations in the Bengawan Solo Hulu Watershed

| Rainfall Stations | Longitude | Latitude | Elevation (m) |
|---|---|---|---|
| Baturetno | 110.929944 | -7.974732 | 148.22 |
| Parangjoho | 110.817714 | -7.951409 | 181.99 |
| Nawangan | 110.897683 | -8.041533 | 247.11 |
| Colo | 110.901000 | -7.750108 | 120.95 |
| Tawangmangu | 111.122547 | -7.666477 | 1003.91 |

In addition to ground-based observations, this study used Global Satellite Mapping of Precipitation (GSMaP) Version 05 rainfall data obtained through Google Earth Engine. Hourly GSMaP data were extracted at the coordinates of each rainfall station and then aggregated into daily rainfall totals from 00:00 to 24:00 to match the temporal resolution of the ground-based observations.

### Dependable Rainfall Analysis

Dependable rainfall was calculated using semi-monthly rainfall data derived from daily ground-based observations and GSMaP data. Each month was divided into two periods, namely Period I and Period II. Dependable rainfall was determined using the Weibull method, as shown in Equation (1).

$$P = \frac{m}{n+1}$$

where (P) is the exceedance probability, (m) is the rank of the rainfall data after being arranged from the highest to the lowest value, and (n) is the total number of data. In this study, dependable rainfall with an 80% exceedance probability (R80) was used [1]. R80 values were calculated for each semi-monthly period using both ground-based observations and GSMaP data.

**Effective Rainfall Estimation**

Effective rainfall was calculated based on the R80 dependable rainfall value. In this study, effective rainfall was defined as effective rainfall for rice cultivation based on the irrigation planning approach. Daily effective rainfall was calculated as 0.7 times the semi-monthly R80 value divided by 15 days, as shown in Equation (2).

$$R_e = 0.7\ x\ \frac{1}{15}\ R80_{(semi-monthly)}$$

where ($R_e$) is the daily effective rainfall (mm/day), ($R80_{(\text{semi-monthly})}$) is the semi-monthly rainfall amount at an 80% exceedance probability (mm), and 15 represents the number of days in one semi-monthly period. The calculation was performed separately for the ground-based observations and GSMaP data to evaluate the capability of GSMaP in estimating effective rainfall.

**GSMaP Performance Evaluation**

The performance of GSMaP against ground-based rainfall observations was evaluated using the correlation coefficient (CC), Percent Bias (PBIAS), Nash–Sutcliffe Efficiency (NSE), and Mean Absolute Error (MAE), as shown in Equations (3)–(6).

$$CC = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2(S_i - \bar{S})^2}}$$

$$P_{Bias} = \frac{\sum(S_i - G_i)}{\sum G_i}\ x\ 100\%$$

$$NSE = 1 - \frac{\sum(G_i - S_i)^2}{\sum(G_i - \overline{G})^2}$$

$$MAE = \frac{1}{n}\sum|S_i - G_i|$$

where $S_i$ represents GSMaP-derived rainfall, $G_i$ represents ground-observed rainfall, $\bar{S}$ and $\bar{G}$ are the mean values of GSMaP-derived and ground-observed rainfall, respectively, and (n) is the number of paired data.

The correlation coefficient (CC) was used to evaluate the degree of association between GSMaP and ground observations. PBIAS was used to identify the tendency of GSMaP to overestimate or underestimate observed rainfall. NSE was used to evaluate the ability of GSMaP to represent the variability of ground-observed rainfall, while MAE was used to measure the average magnitude of absolute errors between GSMaP and ground observations. CC and NSE values closer to 1 indicate better performance, whereas lower PBIAS and MAE values indicate smaller estimation errors.

GSMaP performance was evaluated for actual rainfall at daily, semi-monthly, monthly, and annual scales. In addition, the evaluation was also conducted for effective rainfall calculated from both ground-based observations and GSMaP data. This approach was used to assess changes in GSMaP performance after rainfall data were transformed into effective rainfall.

## RESULTS AND DISCUSSION

**Availability and Characteristics of Rainfall Data**

The initial characteristics of the rainfall data were analyzed to examine data availability and the general rainfall patterns used in this study. As shown in Table 2, the amount of missing data varied among the rainfall stations. Parangjoho had complete rainfall records, while Baturetno had the highest number of missing data, with 935 missing daily records or approximately 26% of the total daily data. Nawangan, Colo, and Tawangmangu had missing data percentages of 21%, 17%, and 20%, respectively. The missing data were filled using the Inverse Distance Weighting (IDW) method before further analysis. In addition, data consistency was evaluated using Double Mass Curve (DMC) analysis.

**Table 2.** Summary of Missing Rainfall Data

| Ground Dataset | Total Daily Data | Missing Data | Missing (%) |
|---|---|---|---|
| Baturetno | 3653 | 935 | 26 |
| Parangjoho | 3653 | 0 | 0 |
| Nawangan | 3653 | 762 | 21 |
| Colo | 3653 | 605 | 17 |
| Tawangmangu | 3653 | 736 | 20 |

Figures 2 and 3 show the semi-monthly rainfall patterns based on ground observations and GSMaP data. In general, both datasets show a similar seasonal pattern, with higher rainfall during the wet season and lower rainfall during the dry season. However, differences in rainfall magnitude are still observed in several periods and stations. This condition indicates that GSMaP is able to capture the general seasonal rainfall pattern, but still contains uncertainty in representing the actual rainfall magnitude at specific times.

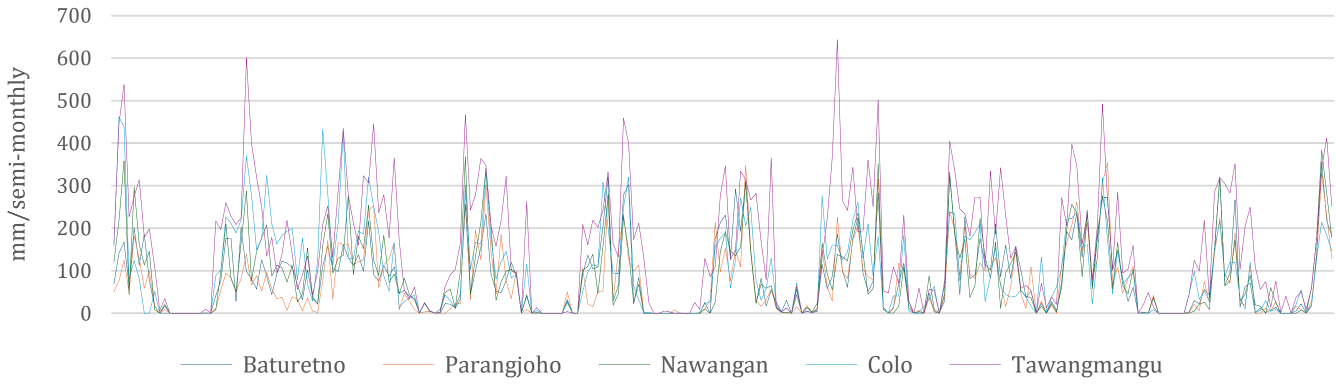


**Figure 2.** Semi-monthly rainfall based on ground observations

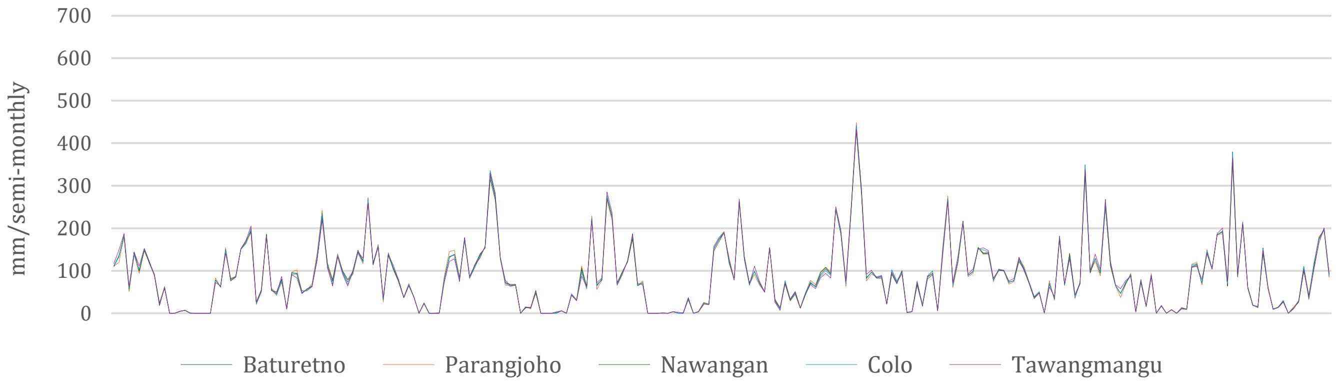


**Figure 3.** Semi-monthly rainfall based on GSMaP data

**GSMaP Performance**

GSMaP performance against ground-based rainfall observations was evaluated at daily, semi-monthly, monthly, and annual scales (Table 3). The evaluation results show that the ability of GSMaP to represent observed rainfall improved as the temporal aggregation scale increased.

**Table 3.** Performance evaluation of GSMaP against ground observations

| GSMaP Dataset | Daily | | | | Semi-monthly | | | | Monthly | | | | Annual | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CC | Bias (%) | NSE | MAE (mm) | CC | Bias (%) | NSE | MAE (mm) | CC | Bias (%) | NSE | MAE (mm) | CC | Bias (%) | NSE | MAE (mm) |
| Baturetno | 0.55 | 9.2 | -0.09 | 5 | 0.82 | 9.2 | 0.47 | 34 | 0.85 | 9.2 | 0.58 | 57 | 0.79 | 9.2 | -0.22 | 328 |
| Parangjoho | 0.61 | 17.2 | 0.08 | 5 | 0.85 | 17.2 | 0.55 | 30 | 0.89 | 17.2 | 0.66 | 48 | 0.72 | 17.2 | -0.69 | 311 |
| Nawangan | 0.61 | -7.9 | 0.17 | 5 | 0.88 | -7.9 | 0.72 | 28 | 0.91 | -7.9 | 0.82 | 45 | 0.94 | -7.9 | 0.76 | 196 |
| Colo | 0.50 | -18.3 | 0.09 | 6 | 0.77 | -18.3 | 0.54 | 40 | 0.80 | -18.3 | 0.60 | 70 | 0.74 | -18.3 | 0.26 | 540 |
| Tawangmangu | 0.45 | -53.7 | 0.11 | 8 | 0.83 | -53.7 | 0.25 | 86 | 0.88 | -53.7 | 0.22 | 167 | 0.93 | -53.7 | -6.03 | 1987 |
| Average | 0.54 | -10.7 | 0.07 | 6 | 0.83 | -10.7 | 0.51 | 44 | 0.87 | -10.7 | 0.58 | 77 | 0.82 | -10.7 | -1.19 | 672 |
| Median | 0.55 | -7.9 | 0.09 | 5 | 0.83 | -7.9 | 0.54 | 34 | 0.88 | -7.9 | 0.60 | 57 | 0.79 | -7.9 | -0.22 | 328 |

At the daily scale, GSMaP produced an average correlation coefficient (CC) of 0.54, PBIAS of -10.7%, NSE of 0.07, and MAE of 6 mm. These values indicate that GSMaP had moderate capability in representing daily rainfall events. The limited performance at the daily scale may be attributed to the characteristics of tropical rainfall, which is often local, short-duration, and highly spatially variable, making it difficult to be accurately represented by satellite estimates.

GSMaP performance improved at semi-monthly and monthly scales. At the semi-monthly scale, the CC increased to 0.83, with an NSE of 0.51. At the monthly scale, the CC further increased to 0.87, with an NSE of 0.58. This improvement indicates that temporal aggregation can reduce the influence of random errors in satellite rainfall data. In other words, although GSMaP does not fully represent individual daily rainfall events, it performs relatively well in capturing rainfall patterns over longer time scales.

At the annual scale, GSMaP produced a CC value of 0.82. This value indicates that GSMaP was still able to follow annual rainfall variation. However, the annual NSE value of -1.19 indicates that accumulated errors in rainfall magnitude remained influential. Therefore, GSMaP was stronger in representing rainfall patterns or variations than in representing absolute rainfall magnitude.

These findings are consistent with previous studies showing that the performance of satellite precipitation products, including GSMaP, can vary depending on region, temporal scale, and topographic conditions. Several studies reported varying daily CC values for GSMaP, such as approximately 0.62 [9], 0.76 [10], 0.76 [19], 0.67 [8] and 0.30 [20]. This variation indicates that GSMaP performance is not uniform across regions. In this study, the daily CC value of 0.54 indicates moderate performance and remains within the range reported in previous studies. However, after aggregation into semi-monthly and monthly scales, the CC increased to 0.83 and 0.87, respectively. This finding reinforces the understanding that temporal aggregation can improve the agreement between satellite rainfall products and ground-based observations.

**Characteristics of Dependable Rainfall**

Dependable rainfall was calculated based on semi-monthly rainfall data using an 80% exceedance probability (R80). The results show a clear seasonal pattern in the study area. R80 values tended to be high during January–March and November–December, while lower values occurred during June–September. This pattern indicates that rainfall availability in the study area is strongly influenced by the seasonal cycle. During the wet season, dependable rainfall was relatively high, whereas during the dry season, dependable rainfall approached zero in several semi-monthly periods.

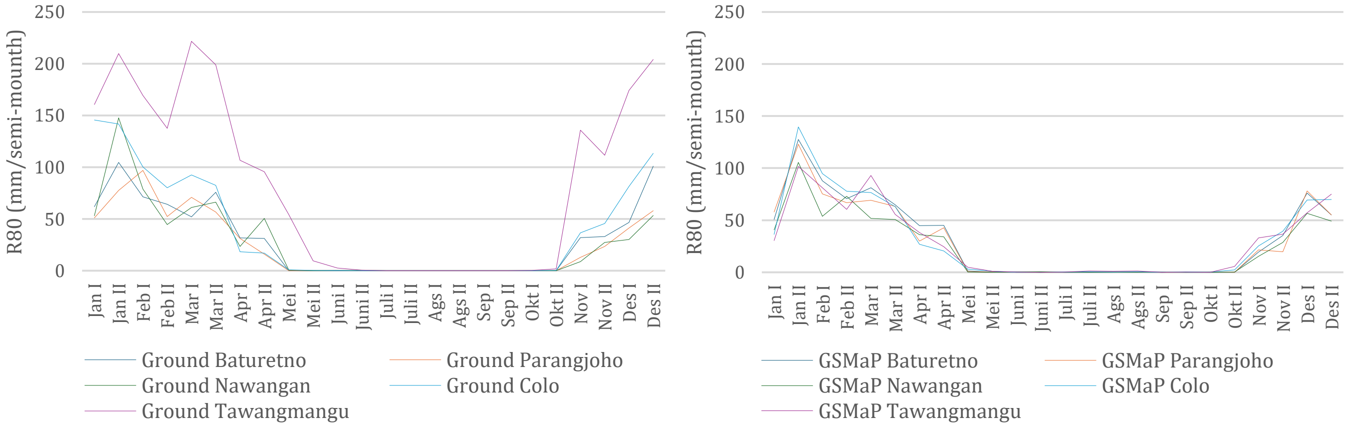


**Figure 4.** Semi-monthly dependable rainfall based on ground observations and GSMaP data

In general, GSMaP was able to represent the seasonal pattern of dependable rainfall. The R80 values derived from GSMaP showed an increase during the wet season and a decrease during the dry season, as shown in Figure 4. This indicates that although GSMaP has limitations in representing daily rainfall, it is still able to capture the long-term rainfall availability pattern required for dependable rainfall estimation.

Effective rainfall was calculated from semi-monthly R80 by multiplying it by a coefficient of 0.7 and dividing it by 15 days. Thus, the resulting effective rainfall values represent daily effective rainfall for rice cultivation. The estimation results show that the GSMaP-based effective rainfall pattern generally follows the effective rainfall pattern calculated from ground observations. Effective rainfall tended to be higher during the wet season and lower during the dry season, as shown in Figure 5. This condition indicates that the long-term statistical information required for effective rainfall estimation can still be represented well by GSMaP.

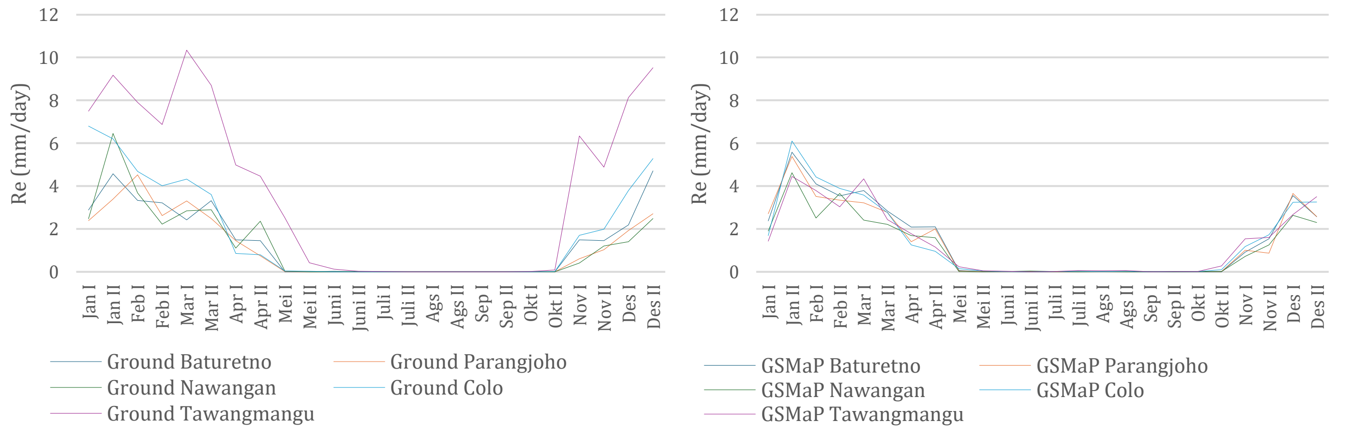


**Figure 5.** Semi-monthly effective rainfall based on ground observations and GSMaP data

**Transformation of Rainfall Data and GSMaP Performance**

The evaluation results in Table 4 show that GSMaP performance improved after rainfall data were transformed into dependable rainfall and effective rainfall. For daily rainfall data, the average CC was only 0.54, with an NSE of 0.07. After the data were processed into dependable rainfall and effective rainfall, the CC increased to 0.92, while the NSE exceeded 0.66.

**Table 4.** Performance evaluation of R80 and daily Re derived from GSMaP against ground observations

| Dataset | R80 | | | | Daily Re | | | |
|---|---|---|---|---|---|---|---|---|
| | CC | Bias (%) | NSE | MAE (mm) | CC | Bias (%) | NSE | MAE (mm) |
| GSMaP Baturetno | 0.92 | 7.9 | 0.81 | 6 | 0.91 | 7.9 | 0.80 | 0.4 |
| GSMaP Parangjoho | 0.92 | 19.9 | 0.77 | 5 | 0.92 | 19.8 | 0.77 | 0.3 |
| GSMaP Nawangan | 0.93 | -7.4 | 0.84 | 6 | 0.92 | -6.7 | 0.84 | 0.4 |
| GSMaP Colo | 0.89 | -21.8 | 0.75 | 7 | 0.88 | -21.9 | 0.74 | 0.5 |
| GSMaP Tawangmangu | 0.94 | -64.7 | 0.17 | 38 | 0.94 | -64.7 | 0.17 | 2.5 |
| Average | 0.92 | -13.2 | 0.67 | 13 | 0.92 | -13.1 | 0.66 | 0.8 |
| Median | 0.92 | -7.4 | 0.77 | 6 | 0.92 | -6.7 | 0.77 | 0.4 |

For dependable rainfall, GSMaP produced an average CC of 0.92, PBIAS of -13.2%, NSE of 0.67, and MAE of 13 mm. For daily effective rainfall, GSMaP produced a CC of 0.92, PBIAS of -13.1%, NSE of 0.66, and MAE of 0.8 mm/day. The high CC values indicate that GSMaP was able to follow the variation patterns of dependable rainfall and effective rainfall calculated from ground observations. Meanwhile, the higher NSE values compared with daily rainfall evaluation indicate that GSMaP-based effective rainfall estimates had better agreement with observation-based estimates.

This improvement indicates that the usefulness of GSMaP should not be assessed only based on its ability to represent actual daily rainfall. In dependable rainfall analysis, rainfall data are ranked according to their probability of occurrence, making random errors in daily rainfall events less dominant. As a result, although differences exist between GSMaP and ground observations at the daily scale, the long-term statistical characteristics used to calculate R80 and Re can still be represented reasonably well.

Therefore, the transformation from actual rainfall into dependable rainfall and effective rainfall can be understood as a process that reduces part of the uncertainty in satellite rainfall data. This explains why GSMaP performance in estimating effective rainfall was better than its performance in estimating daily rainfall.

**Implications of Using GSMaP for Effective Rainfall Estimation**

Figure 6 shows the average daily effective rainfall from all stations for each semi-monthly period. In general, the GSMaP-based effective rainfall pattern follows the effective rainfall pattern derived from ground observations, particularly in representing wet and dry periods. However, GSMaP tends to produce lower values than ground observations in several wet-season periods, especially at the beginning and end of the year. This is consistent with the negative PBIAS value in the effective rainfall evaluation, which indicates a tendency toward underestimation.

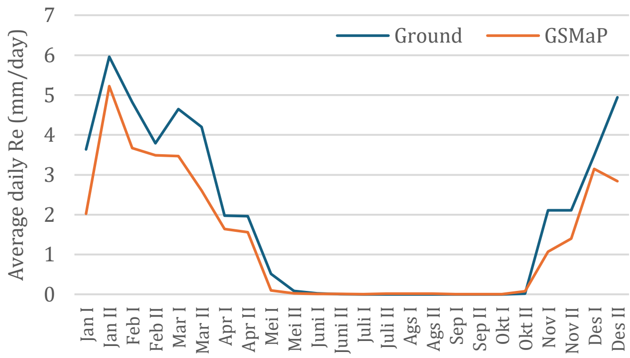


**Figure 6.** Average daily Re based on ground observations and GSMaP data

Figure 7 shows the average daily effective rainfall after excluding the Tawangmangu station from the calculation. The pattern between ground observations and GSMaP becomes closer than the average pattern of all stations shown in Figure 6. This condition indicates that the Tawangmangu station has a considerable influence on the difference between GSMaP-based and observation-based effective rainfall estimates. This may be related to the much higher elevation of Tawangmangu compared with the other stations, which can increase uncertainty in satellite rainfall estimation over more complex topographic areas.

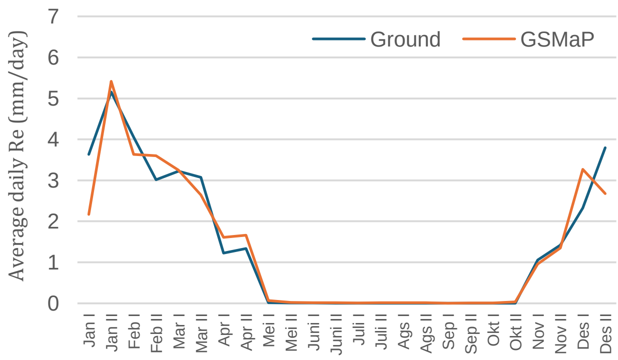


**Figure 7.** Average daily Re (excluding Tawangmangu station) based on ground observations and GSMaP data

The results of this study indicate that GSMaP has the potential to be used as an alternative data source for effective rainfall estimation, particularly in regions with limited ground-based rainfall observations. Although GSMaP is not fully accurate in representing daily rainfall events, it can provide good results for analyses based on long-term rainfall patterns, such as dependable rainfall and effective rainfall.

In the context of water resource management, this finding is important because effective rainfall is more directly related to crop water availability than actual daily rainfall. Therefore, GSMaP can be used to support water availability analysis, irrigation planning, and agricultural water management, especially in areas without adequate rainfall station networks.

However, the use of GSMaP should still consider the purpose of the analysis. For daily rainfall events or short-duration extreme rainfall analysis, GSMaP performance needs further evaluation because its accuracy at the daily scale remains moderate. In contrast, for dependable rainfall and effective rainfall estimation, GSMaP shows better performance and greater potential for practical use.

## CONCLUSION

This study evaluated the capability of GSMaP satellite rainfall data to estimate effective rainfall using ground-based rainfall observations from five stations around the Bengawan Solo Hulu Watershed during the 2015–2024 period. The results showed that GSMaP had moderate performance in representing daily rainfall, with CC and NSE values of 0.54 and 0.07, respectively. However, GSMaP performance improved at longer temporal aggregation scales, particularly at the semi-monthly and monthly scales, with CC values of 0.83 and 0.87, respectively.

The R80 dependable rainfall results showed that GSMaP was able to represent the seasonal pattern of rainfall availability in line with ground observations. GSMaP-based effective rainfall estimates also showed good agreement with observation-based estimates, with CC reaching 0.92 and NSE exceeding 0.66. These findings indicate that transforming rainfall data into dependable rainfall and effective rainfall can reduce part of the error influence in satellite rainfall data.

Based on these results, GSMaP has the potential to be used as an alternative data source for effective rainfall estimation, particularly in regions with limited ground-based rainfall observations. However, the use of GSMaP for daily rainfall analysis should still consider the purpose of the analysis, as its performance remains lower than that for dependable rainfall and effective rainfall estimation.

## ACKNOWLEDGMENTS

The authors would like to thank BBWS Bengawan Solo for providing rainfall observation data.

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