Validation of Climate Hazard Group InfraRed Precipitation with Station (CHIRPS) Data in Wonorejo Reservoir, Indonesia

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Abstract. This study aims to test the validation of precipitation data from CHIRPS compared to measurement data. The study location is Wonorejo Reservoir, Indonesia. The methods in this research were 1) data quality test with the consistency test and stationary test, and 2) validity test with parameters of NSE value and correlation. The study results show that 1) The data quality test shows that the precipitation data from CHIRPS are consistent and homogeneous; 2) The validity test is carried out in two stages, for uncorrected data and corrected data. According to NSE value, the validity test results on uncorrected data shows that CHIRPS's precipitation data are unsatisfactory. When viewed from the correlation, the precipitation data from CHIRPS has a very strong relationship to precipitation measurement data. The next step is to test the validity of the corrected data. The validation test of corrected data shows that precipitation data from CHIRPS is satisfactory according to NSE value. Moreover, the precipitation data from CHIRPS strongly correlates with the precipitation measurement data. This study indicates that the precipitation data from CHIRPS can be utilized as alternative precipitation data if measurement data are limited.

Keywords: CHIRPS, google earth engine, precipitation, reservoir, Wonorejo

1. Introduction
Rainfall data is one of the important parameters in hydrological modeling [1] [2]. Accurate rainfall data, whether temporal or spatial, is very much required in predicting extreme weather conditions, floods, droughts, hydrology, agriculture, irrigation, and water resource management [3] [4] [5] [6] [7] [8]. Accurate and reliable collection of rainfall data becomes a challenging demand for hydro-climatological analysis in developing countries and mountainous areas [9] [10] [11] [12]. Ground measurement precipitation, radars, and satellites comprise popular methods to estimate rainfall in a certain region. Ground measurement precipitation is the primary approach to obtain rainfall information because they measure rainfall directly on the ground. Therefore no kinds of signals need to be converted or corrected. However, the availability of ground measurement precipitation networks is rare, and the spatial coverage is irregular. In some regions of the world, these are non-existent, which is also true for the most remote
areas in Indonesia.

The country of Indonesia has a large area. It causes the infrastructure condition to be uneven in several regions, particularly for remote areas, such as the unavailability of ground measurement precipitation. However, rainfall data that are complete, accurate, and of a high density are required in the analysis of weather and climate forum, such as what occurs for Wonorejo Reservoir, East Java, Indonesia. The ground measurement precipitation that affects calculations for the Wonorejo Reservoir is located far apart, which will affect the level of data accuracy. The availability of data is relatively minimal due to the presence of damage on the rainfall measurement tool. In overcoming these problems, we need an alternative to obtain a solution to know rainfall conditions and get the required rainfall data.

Many researchers have stated that rainfall estimation is based on satellite imagery and re-analysis data with various high spatial and temporal resolutions. They stated that the rainfall data obtained from the satellite have the potential to supplement the discrepancy or even to be able to replace the data that could be obtained directly from Ground measurement precipitation [1] [13] [14]. Satellite rainfall data with global spatial coverage, high temporal resolution (up to approximately every 3 hours), and high spatial resolution (up to 4 km) [15] [16] [17] may be considered as a replacement for rainfall data in regions that do not have ground measurement precipitation. An example is the Climate Hazard Group InfraRed Precipitation with Station (CHIRPS) [18] [19] [20] [21] [22].

Climate Hazard Group InfraRed Precipitation with Station (CHIRPS) is the precipitation data obtained from the CHIRPS meteorological satellites. The rainfall estimation data was introduced as reanalyzed data with a spatial resolution of 0.05° x 0.05° arc degrees, or equivalent to 5 km. CHIRPS comprises a blend of satellite-only data Climate Hazard Group InfraRed Precipitation with Station with ground measurement precipitation. Satellite rainfall data CHIRPS is obtained through a cloud-based geospatial platform, the Google Earth Engine (GEE). This data may be utilized if several methods of testing have been conducted, as data calibration and validation. Validation is performed by comparing data from ground measurement precipitation and satellite data to obtain certain appropriateness with NSE value and correlation coefficient parameters to determine the appropriateness level between the two data sets. This research aims to validate rainfall data taken from the satellite data of Climate Hazard Group InfraRed Precipitation with Station (CHIRPS).

Figure 1. Research Location
2. **Materials and Methods**

The study location is the Wonorejo Reservoir, located in Tulungagung Regency in East Java, Indonesia. This reservoir has a surface area of 380 hectares and a capacity of approximately 122 million m$^3$. Wonorejo Reservoir is a multipurpose reservoir that functions to supply raw water, generation of electrical power, flood control, and development of land fishery and tourism.

The utilized data are taken from ground measurement precipitation and the satellite. Data from the ground measurement precipitation were obtained through measurement using ground measurement precipitation present in the Bendungan rain gauge station, Bagong rain gauge station, and Pagerwojo rain gauge station (Figure 1). The data were obtained through management institutions: the Meteorology, Climatology, and Geophysics Agency of Karangploso, and the Public Company of Jasa Tirta 1. The utilized length of data is 16 years within the year range of 2004-2019, consisting of monthly data. Meanwhile, satellite rainfall data used the CHIRPS satellite. The satellite data were downloaded from the facility of Google Earth Engine (GEE).

CHIRPS data is rainfall data with a spatial resolution of 0.05° x 0.05° that were obtained through Google Earth Engine. Google Earth Engine is a computational platform that allows users to perform geospatial analysis.

The following are the steps in conducting this research:

1. Consistency testing of measured rainfall data (utilizing the Double Mass Curve method) and satellite rainfall data (using the method of Rescaled Adjusted Partial Sums (RAPS)) [23].
2. Data quality tests are using F-test and T-test methods. The objective of these tests is to find out the stability of variance values in the data and the mean value.
3. Analysis of regional rainfall to find out the influence of the utilized rainfall stations. The method used was Thiessen Polygons.
4. Test the suitability of uncorrected and corrected data to analyze the comparison of measurement data and satellite data. The methods were Root-Mean-Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Correlation Coefficient, and Relative Error.
5. Satellite data were corrected using selected regression equations. The used regression equations were exponential regression, linear regression, logarithmic regression, polynomial regression, and power regression to optimize parameter values in increasing coherence among hydrological responses.

The Root-Mean-Square Error (RMSE) value can be calculated with the following equation: [24]

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2}$$  

The representation of $n$ is the total data, and $e_i$ is the difference between observed rainfall and satellite rainfall.

The Nash-Sutcliffe Efficiency (NSE) value can be calculated with the following equation: [25]

$$NSE = 1 - \frac{(P_1-P_2)^2}{(P_1-P)^2}$$  

The representation of $P_1$ is the observed rainfall, while $P_2$ is the satellite rainfall data.

The correlation coefficient can be calculated with the following equation: [26]

$$r = \frac{n\sum PR-\sum P \sum R}{\sqrt{n\sum P^2-\sum P^2}[n\sum R^2-(\sum R)^2]}$$  

$P$ represents the observed rainfall, while $R$ is the satellite rainfall data.

The relative error value can be calculated with the following equation:

$$KR = \frac{\sum_{i=1}^{N} (P_i-Q_i) / P_i \times 100\%}{\sum_{i=1}^{N} P_i}$$  

The relative error value is used to determine the comparison between variables. The representation of \( P_i \) is the observed rainfall, while \( Q_i \) is the satellite rainfall data.

Preparation of satellite data utilizing the Google Earth Engine (GEE) comprises:
1. Creating watershed boundaries in the form .shp, .dbf, or .shx data.
2. Uploading of .shp, .dbf, or .shx data to Google Earth Engine (GEE).
3. Inputting the contents of .shp, .dbf, or .shx data to the script menu.
4. Run the program.
5. Download the data in the form of numbers and charts.

3. Results and Discussion

Quality Testing of Rainfall Data with Consistency Testing and Stationary Testing

Data quality analysis is required in statistical data analysis for data in periodic series such as rainfall data. This analysis was utilized to find out the statistical quality of the hydrological data because the data collection process on the field certainly may experience disruption from various factors such as environmental factors and human factors that will affect the data results. Data that has passed the presumptive test stage has good statistical data quality for subsequent hydrological analysis.

Consistency testing was utilized to determine whether changes had occurred in the data affected by environmental factors or measurement methods. Stationary testing was used to determine the stability of data variance values and the stability of average data values. Consistency testing utilized the double mass curve method. All the data that had gone through consistency testing showed consistent results, and therefore are feasible to be used in the next analysis process of stationary testing. Stationary testing utilized F-test and T-test for observed data and satellite data. Stationary testing is successful if the results are homogeneous with a variance stability value and average stability value being stable, where \( F_{\text{count}} < F_{\text{critical}} \) and \( T_{\text{count}} < T_{\text{critical}} \).

| No | Station Name | Angle Before Correction | Correction Factor | Corrected Angle | Remarks |
|----|--------------|-------------------------|-------------------|-----------------|---------|
| 1  | Bendungan    | 39.87°                  | 1.271             | 46.30°          | Consistent |
| 2  | Pagerwojo    | 58.88°                  | 0.572             | 47.22°          | Consistent |
| 3  | Bagong       | 36.01°                  | 1.488             | 43.53°          | Consistent |

Table 1 indicates that all rain gauge stations required correction with a correction factor of 0.572-1.488, depending on the locations of the rain gauge stations. After undergoing the correction process, all the stations possessed corrected angles according to the stipulation of within the value range of \( 42^\circ < \alpha < 48^\circ \), and thus it can be said that the rainfall data for each of the rain gauge stations are consistent.

Consistency testing of CHIRPS satellite data utilized Rescaled Adjusted Partial Sums (RAPS) because the available data comprises singular data.

| Period | \( Q_{\text{count}} \) | \( Q_{\text{critical}} \) | \( R_{\text{count}} \) | \( R_{\text{critical}} \) | Remarks |
|--------|------------------------|--------------------------|------------------------|------------------------|---------|
| Monthly| 0.322                  | 1.220                    | 0.489                  | 1.620                  | Consistent |
| 3-Month| 0.313                  | 1.262                    | 0.618                  | 1.522                  | Consistent |
| 6-Month| 0.469                  | 1.198                    | 0.768                  | 1.430                  | Consistent |
| Annual | 0.655                  | 1.188                    | 1.174                  | 1.370                  | Consistent |
Based on Table 2, it was found that the results of RAPS testing for all periods with a confidence level of 5% showed consistent results because $Q_{\text{count}}$ and $R_{\text{count}}$ are smaller than $Q_{\text{critical}}$ and $R_{\text{critical}}$.

### Average Regional Rainfall

Rainfall data of CHIRPS that was obtained through the GEE platform comprises regional average rainfall data. Thus the measured data from the three rain gauge stations must be calculated to obtain the regional average rainfall data using Thiessen Polygons. The objective of this process is to be able to compare the measured data and satellite data. The results obtained from the depiction of Thiessen Polygons are in the form of areas of influence of each rain gauge station toward the watershed (Figure 2). The values of the areas of influence are multiplied by the measured rainfall to obtain the final resulting regional average rainfall (Table 3).

![Figure 2. Map of Areas of Influence of Rain gauge stations with the Method of Thiessen Polygons](image)

| No | Rain gauge station | Area ($\text{Km}^2$) | $K_r$ |
|----|--------------------|----------------------|------|
| 1  | Bendungan          | 42.817               | 0.963|
| 2  | Bagong             | 0.255                | 0.006|
| 3  | Pagerwojo          | 1.375                | 0.031|
|    | **Total**          | **44.447**           | **1.000**|

### Appropriateness Testing of Uncorrected Data

Appropriateness testing of uncorrected data was utilized to determine the magnitude of the data appropriateness level that resulted between the measured rainfall data and satellite rainfall data that have not been corrected. The methods were Root-Mean-Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Correlation Coefficient, and Relative Error [27]. The utilized data ranges were 16 years, 12 years, 13 years, 14 years, and 15 years in this research.
Table 4. Summary of Appropriateness Testing of Uncorrected Data

| Data Range | RMSE Value | RMSE Interpretation | NSE Value | NSE Interpretation | Kr Value | Kr Interpretation | R Value | R Interpretation |
|------------|------------|---------------------|-----------|--------------------|----------|-------------------|---------|-----------------|
| 16 yr.     | 7.007      | Unsatisfactory      | 0.931     |                    | 0.810    | Strong             | 0.713   | Strong          |
| 12 yr.     | 7.594      | Unsatisfactory      | -1.825    |                    | 1.019    | Strong             | 0.710   | Strong          |
| 13 yr.     | 7.483      | Unsatisfactory      | -1.516    |                    | 0.911    | Strong             | 0.684   | Strong          |
| 14 yr.     | 7.305      | Unsatisfactory      | -1.133    |                    | 0.830    | Strong             | 0.681   | Strong          |
| 15 yr.     | 7.123      | Unsatisfactory      | -1.010    |                    | 0.813    | Strong             | 0.698   | Strong          |

Based on Table 4, the highest RMSE value was the rainfall data for the 12-year calibration. The NSE value showed a result of “Unsatisfactory” for all year periods because NSE < 0.36, including categories that did not satisfy statistical calibration standards. The magnitude of the Kr value for each period ranged from 80% - 100%. Therefore, the validation of CHIRPS rainfall data that have not been corrected with the measured rainfall data possessed a high relative error. However, all the rainfall data resulted in strong correlation values.

![Figure 3](image-url)
Regression Analysis
Regression analysis was utilized to determine correction factors for satellite data using a calibration stage [Sangati, 2009]. The calibration step was performed by creating scatterplots of the measured rainfall data and satellite rainfall data. The calibration resulted in 5 equations, and only one equation was utilized as the correction factor, which was the one with the greatest correlation coefficient (R) value. The used data period was the monthly period, with the utilized data ranges for calibration being 16 years, 12 years, 13 years, 14 years, and 15 years.

Based on the calibration results with scatterplots, the highest correlation coefficient (R) value was for the power equation with an R-value of 0.70. Therefore, the equation utilized for the data correction method with the validation method was the power equation.

Appropriateness Testing of Corrected Data (Data Validation)
After obtaining the highest R-value through the calibration stage, the next process was performing data validation tests with the four parameters of Root-Mean-Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Correlation Coefficient, and Relative Error. The utilized period was the monthly periods with data ranges of 4 years, three years, two years, and one year (different data from the calibration process).

| Data Range | RMSE | NSE Value | Kr Value | R Value | Interpretation |
|------------|------|-----------|----------|---------|----------------|
| 4 Years    | 4.623| 0.420     | 0.257    | 0.792   | Very Strong    |
| 3 Years    | 4.163| 0.552     | 0.186    | 0.845   | Very Strong    |
| 2 Years    | 2.403| 0.794     | 0.229    | 0.946   | Very Strong    |
| 1 Year     | 3.298| 0.601     | 0.144    | 0.810   | Very Strong    |

Based on the validation results for corrected data in Table 5, the highest RMSE value was for rainfall data with a data range of 4 years. Based on the established standards for NSE values, the NSE value showed a “Satisfactory” for all data ranges with monthly periods for the results of the corrected data. The magnitude of the Relative Error value for each period ranged from 10% - 25%, which meant that the validation of corrected data showed success because the resulting relative error value was very small, and the Correlation Coefficient improved from “Strong” to “Very Strong.”

4. Conclusion
In brief, a comparison was performed to estimate monthly rainfall from the CHIRPS product with in situ observations from the three observation stations located in Wonorejo Reservoir, Indonesia. The utilized data were from the period of 2004-2019 (16 years). The suitability analysis between satellite data and measurements uses statistical analysis, namely Root Squared Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Correlation Coefficient, and Relative Error.

Based on the results of calculations that had been performed for the data correction, it was found that the measured rainfall data and CHIRPS satellite rainfall data showed increased values from the prior data. Results of corrected validation showed very good deals for the measured rainfall data and satellite rainfall data, with closely approximating results. It can be proven that through the NSE values for all the utilized data ranges, the resulting correlation is very strong. Therefore, it can be concluded that the measured rainfall data and satellite rainfall data possess a high level of appropriateness. Thus the satellite data may be utilized as a replacement alternative or supplement for unavailable data of on-the-field measurements.

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