Assessment of satellite-based precipitation data for SWAT+ modelling in upstream catchment of Bengawan Solo, Java, Indonesia

Bachelor Thesis for Civil Engineering at the University of Twente

Conducted by:

Vinsensius Windy Hermawan

September 2023

UNIVERSITY OF TWENTE.

UNIVERSITAS INDONESIA
Veritas, Probitas, Iustitia | Est. 1849

Date: September 7th 2023

Conducted by:

Vinsensius Windy Hermawan
s2426994
vinsensiuswindyhermawan@student.utwente.nl

Supervised by:

University of Twente
m.j.booij@utwente.nl

University of Indonesia
Andry Rustanto, S.Si., M.Sc.
rustanto@ui.ac.id

UNIVERSITY OF TWENTE.

UNIVERSITAS INDONESIA
Veritas, Probitas, Iustitia | Est. 1849

Preface

This report will mark the milestone of my four-year journey at the University of Twente. Throughout these four years, I feel grateful for the support that always comes from my family. To my beloved parents, Mom and Dad, since the beginning, have given me guidance for studying abroad and also support through prayers and advice whenever I am facing difficulties that have been my constant companions. To my dear sister, Kesia and my little brother, Deven who had time to accompany me during the execution of this research. To my girlfriend Diana, who is always there listening to all my difficulties and offers words of encouragement have been the motivation for me to keep going. And for all my friends in Enschede especially for 'Geng yahut' and 'PPI Camelot', that always became a place called 'home' during my study in Enschede.

Moreover, I would like to express my deepest appreciation to my supervisor, Martijn Booij for the opportunity to conduct my bachelor assignment at the University of Indonesia. His expertise, encouragement and feedback always helped me to achieve the goals of this research. To my supervisor from the University of Indonesia, Andry Rustanto for his kindness and countless help during the execution of this project. Without his guidance, I could not finish this project as expected. Finally, I hope this research will be helpful especially for the application in my home country, Indonesia.

Vinsensius Windy Hermawan
Jakarta, September 7th, 2023

Summary

Hydrology is a scientific field that deals with water resources aiming to understand its occurrence, distribution and impact towards the environment. To have a better perspective on how these processes work, hydrological modelling is often used as a tool to analyze the phenomena that occur in certain areas and is commonly used to examine the impact of certain interventions for water resources. As one of the crucial inputs for hydrological modelling, precipitation data plays an important role that could directly affect the performance of the hydrological models. However, due to limitations, the precipitation data availability is often inadequate or even unavailable in certain areas. One of the examples was found in the upstream Bengawan Solo catchment, Indonesia, where the precipitation data is inadequate. One of the options to overcome this problem is using satellite precipitation products to replace the in-situ data. However, there are various numbers of satellite precipitation products globally. Different products have different characteristics of precipitation data. Therefore, this research was conducted mainly to investigate the performance of the satellite precipitation products (SPPs) especially in the application for hydrological modelling. The satellite precipitation products investigated in this research are the Climate Prediction Center Morphing Technique (CMORPH) and the Multi-Source Weighted Ensemble Precipitation (MSWEP).

In comparison with the observed precipitation from 12 in-situ stations, MSWEP satellite precipitation products with a smaller grid size show a higher performance compared to CMOPRH satellite products. This was identified with BIAS and MAE indicators that show lower values for MSWEP satellite product compared to CMORPH product. Moreover, in the application for SWAT+ hydrological model, the streamflow generated using MSWEP satellite product also shows a higher performance both for comparison with the observed streamflow and the streamflow generated by the same model using observed precipitation. Thus, the MSWEP precipitation product is corrected using a bias correction technique called quantile mapping. However, the results of the bias correction data do not show many improvements for the comparison with observed precipitation or for the streamflow generated using the corrected data.

Table of Contents

1. Introduction

1.1. Background and Motivation

Hydrology is a scientific field that deals with the water resource on earth regarding its occurrence, distributions and the circulation also the chemical which has impacts towards the environment (Reddy, 2005). In practice, hydrology is often used to understand the impact of rainfall phenomena such as water supply, water quality, irrigation, flooding predictions, river discharge, and so on (Jajarmizadeh et al., 2012). Referring to Bergström (1991), advancing computer technology and mathematical model helped the development of hydrological models able to accurately simulate the actual phenomena in an area. Hydrological modelling is often used as a planning tool for water management. However, one of the rising problems of hydrological modelling is data scarcity. For instance, Sun et al. (2018) addressed that precipitation data could be inadequate for hydrological model due to the inexistence or uneven distribution of rain gauge stations (in situ stations). This is crucial because precipitation data directly influence the performance of the model. As a result, inadequate precipitation data could mislead the model into the inference of the results (Kauffeldt et al., 2013).

One of the alternatives to substitute the in-situ measurement to obtain precipitation is using a satellite to predict the rainfall from observation in the atmosphere. These satellites estimate the rain using infrared and microwave sensors that capture the energy and water vapour streaming around the atmosphere (Kidd & Levizzani, 2011). Currently, these satellite products are available globally and with advanced spatial and temporal resolutions, which could be used efficiently for hydrological modelling compared to in-situ measurement (Maggioni & Massari, 2018). However, due to the spatial and temporal resolutions of each satellite product, the accuracy of the precipitation prediction is also diverse. Finding satellite products that predict the most accurate precipitation needs more in-depth analysis and application in hydrological modelling to observe the feasibility of these products. A paradigm shift might arise if these products are considerably precise in predicting the precipitation and feasible for application in modelling. If the satellite precipitation products can precisely predicting the precipitation in certain area, it could be possible to use the satellite products in hydrological modelling and replacing the in-situ measurement for the precipitation data.

1.2. State of the art

1.2.1. Satellite Precipitation Product

Precipitation or rainfall data is the most influential forcing variable that directly determines the output of a hydrological model (Beck et al., 2017). On the other hand, Beck et al. (2016) argues that estimating the precipitation in certain area using modelling is challenging due to spatiotemporal heterogeneity. Michaelides et al. (2009), describes there are four main paths to obtain precipitation data for hydrological modelling. The first approach is to do a ground measurement using a rain gauge, which is the most accurate way to get the precipitation data. Another ground measurement is using a ground radar that can be observed remotely. The third option is to use a satellite sensor to derive the rainfall data. The last option is using atmospheric retrospective-analysis models. However, ground measurement is sometimes more complex to do in some area and sometimes require cost that relatively high. Due to these consequences, there are exist areas where precipitation data is unavailable due to inexistence of ground measurement. On the other hand, the satellite precipitations products can easily provide the precipitation data and available almost for all area around the world. For example, satellite precipitations products often used to obtain the precipitation around the ocean where ground measurement is unavailable.

According to Salvadore et al. (2015), the emergence of satellite technology has made the precipitation data obtained from satellite more adequate and accessible for modelling. There are several satellite precipitation products (SPPs) that exist globally. For example, Liu et al. (2020) summarized six satellite missions providing precipitation data such as (i) Tropical Rainfall Measuring Mission (TRMM), (ii) Global Precipitation Measurement (GPM), (iii) NOAA National Center for Environmental Prediction (NCEP) and Climate Prediction Center (CPC) that merged for IR project, (iv) MERRA-2 and Global and Regional Land Data Assimilation Projects, (v) TROPICS and (vi) Datasets for Tropical Meteorology and Climatology. Each of these missions provides precipitation data using a different approach to elaborate data from satellite sensors. However, the TRMM project ended in April 2015 after serving for 17 years providing the precipitation data. The project itself continued by the GPM project that orbited in July 2014 with more advanced technology to observe precipitation. Polong et al. (2022), in study at the Upper Tana River basin of Kenya, assess four satellite precipitation products (SPPs), namely, (i) Academic Research Consortium (ARC)-2, (ii) Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS v2.0), (iii) TMPA

3B42v7 that obtained from TRMM satellite and (iv) Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record (PERSIANN-CDR). This study concluded that ARC-2 datasets have the highest performance in several tests, followed by CHIRPS and TRMM.

Aiming to better understand these satellite products, Beck et al. (2017) assessed 22 satellite precipitation products (SPPs) which were grouped into two different types. One of the groups consisted of 9 SPPs that corrected using gauges data and the other group consisted of 13 SPPs that were not corrected and only relied on the satellite data. The uncorrected SPPs are evaluated using gauges observations as the reference and the corrected SPPs are tested using a hydrological model. In the uncorrected satellite precipitation result, MSWEP-ng v2.0 shows the lowest mean error against the ground gauges precipitation data for a short measurement period. For long-term precipitation measurements, CHIRPS v2.0, MSWEP-ng v1.2 and v2.0 shows the same level of highest accuracy compared to the other products. For the corrected satellites products, hydrological modelling was used using each product and the generated streamflow was compared with the observed streamflow. The result of the model is presented based on Nash-Sutcliffe Efficiency as an indicator and it was found that for example, in tropical areas, MSWEP V2.0 is showing the best performance followed by MSWEP v1.2 and CHIRPS v2.0.

Clearly, due to different methods and technology used for obtaining the data, the spatial and temporal resolutions of each product is diverse among one and another which gives a range of uncertainty in the data (Lee et al., 2023). Moreover, the accuracy of the SPP is highly influenced by the area where the product will be implemented. Therefore, all SPPs from various studies will be listed in Table A. 1 for consideration in further analysis. In this table, each row represents the best satellite precipitation product from an assessment and comparison to other products in the corresponding studies.

1.2.2. Satellite Precipitation in Hydrological Modeling

Hydrological modelling can be summarized as an attempt to understand and simulate the reality of the hydrological process in an area starting from the precipitation to the runoff process (Cherif et al., 2023). According to Pechlivanidis et al. (2013), hydrological modelling can be used for several purposes based on the problem defined in the field such as extreme conditions (drought or flooding) and water management in general. In their studies about socio-hydrology, Blair and Buytaert (2016) indicate that hydrological modelling is not only an attempt to understand the physics of water but is also related to socio-economic aspects where the hydrological model is often considered as the background consideration for socio-economics decision making. This reason shows the importance of a hydrological model's performance in representing the actual conditions in the application area.

However, it is often found that the hydrological model has a low performance due to uncertainties from input data, model structure and boundary conditions which are mainly caused by limited data and weak knowledge of hydrological modelling. Due to these limitations, the accuracy and quality of the simulated prediction are threatened (Song et al., 2015). As discussed in the previous section, precipitation is a highly prominent variable in the model. Due to limitations and challenges to obtain accurate precipitation from ground measurements, remote sensing data could be the easiest choice to get precipitation data. However, remotely sensed data does not give a direct measure of the aimed variable (precipitation) because it was derived from the observations using satellite infrared or in the electromagnetic microwave spectrum obtained at the top of the cloud. Therefore, using this method, the precipitation data is estimated where data biased estimate could exist (Tarek et al., 2020).

Currently, there are various studies about the application of satellite-based precipitation in hydrological modelling. One of the applications has been conducted by Su et al. (2021), where satellite-precipitation products, namely TMPA 3B42 and IMERG are used for hydrological simulation in catchment at the southern part of China. Yuan et al. (2017) uses TMPA and IMERG datasets for streamflow simulation in Chindwin River Basin, Myanmar. However, the TMPA dataset used is TMPA 3B42v7 where more improvement is included in this version. The results shows that both datasets are capable of simulating the streamflow in the area although showing considerable errors. In both studies, the error was fixed with a bias-correction method that eventually led to better results. Moreover, Peng et al. (2021) also performed a correction method for PERSIANN-CDR, CHIRPSv2.0, CMORPH, IMERG, GSMaPv6, and TMPA 3b42v7 datasets for application in Tarim Basin Hydrological model at China. The results show that all corrected datasets have a better performance compared to the raw data. Still, the satellite product has advantages and disadvantages even after being corrected. These studies confirm that satellite precipitation products are applicable for hydrological modelling.

Nevertheless, the performance of the hydrological model is strongly driven by the accuracy of the corresponding satellite precipitation product which is diverse in different regions (Chen et al., 2019). Therefore, choosing suitable product is crucial and a bias-correction method is still needed to reduce the inaccuracy of precipitation prediction.

1.3. Research Gap

Understanding hydrological processes is crucial for better water management planning. Often, hydrological modelling is used to get information about water characteristics in study area. The hydrological model needs several specific inputs such as precipitation. With accurate precipitation data, the model will have a better representation of the actual conditions. However, precise precipitation data from ground measurements are frequently not available. One example of this problem is found at the upstream Bengawan Solo catchment in Java, Indonesia. The existence and quality of ground measurement data are still questionable (Auliyani & Wahyuningrum, 2021).

One of the alternatives is to use satellite-based precipitation data as the input for the model. There are several options available for satellite-based datasets for the model. It cannot be avoided that the satellite-based data might generate a biased estimation of the precipitation. Moreover, there is still minimum research on satellite precipitation for hydrological modelling, especially in Indonesia. Therefore, it is crucial to assess these satellite datasets to find out which one is suitable and feasible for application in hydrological modeling.

1.4. Study Area

As seen in Figure 1, the study area is called the upper Bengawan Solo (UBS) catchment and is located on the most populated and vital island in Indonesia. The catchment is in Central Java province and Yogyakarta province. The total surface area of the catchment is $3{,}306.5\ km^2$ which corresponds to approximately 20,5% of the total Bengawan Solo Catchment (Rustanto et al., 2017) which is regarded as the largest catchment in Java. According to Suroso et al. (2023), the Bengawan Solo catchment plays an essential role because the area is mainly used for agricultural use. The water captured from this catchment is discharged to the Bengawan Solo River. The catchment itself is prone to extreme conditions. Drought is often occurring in dry periods. On the other hand, due to the high intensity of rainfall during the wet season, flooding is also often occurring (Rustinsyah et al., 2021). Therefore, understanding the hydrology in this area is vital for supporting tools in decision-making.

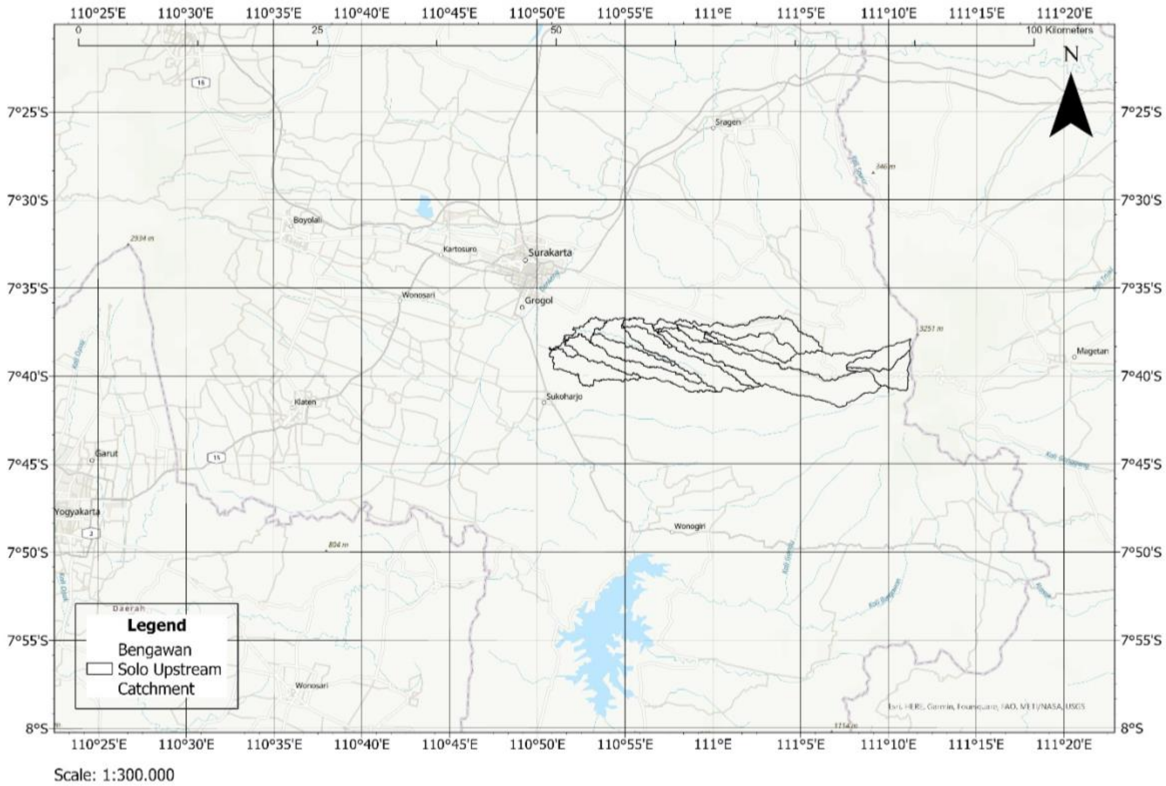

Figure 1. The study area

1.5. Research Objective

‘To compare the precipitation and the simulated streamflow using observed and satellite-based data for SWAT+ hydrological model application in the Bengawan Solo upstream catchment in Java, Indonesia.’

1.6. Research Questions

To achieve this objective, four research questions is derived:

1. What is the accuracy of the satellite-based precipitation data compared to the observed precipitation?
2. What is the accuracy of the model that used observed precipitation compared to the observed streamflow?
3. What is the performance of the model that used satellite-based precipitation data compared to streamflow generated by the model using observed data?
4. What is the performance of the model using uncorrected and bias-corrected satellite-based precipitation data by comparing the streamflow generated by the model using observed data?

The first research question is the verification of satellite precipitation against the observed precipitation. The selected satellite precipitation products (SPPs) will be checked by several indicators to determine the accuracy of the satellite predictions against the observed precipitation. The second and third research questions are mainly focusing on hydrological modelling, where the outcomes of the model will be evaluated. The second research question will assess the performance of the model that uses the observed precipitation as the input. The result obtained from the model (streamflow) will be compared with the observed streamflow. The third research question will use satellite precipitation as the input of the model. The result of the model that uses the satellite precipitation will be compared to the streamflow obtained from the model that uses the observed precipitation as conducted in the second research question. The last research question will require an extra step to analyze and perform a bias-correction method for satellite precipitation. After the satellite precipitation is corrected, it will be implemented in the model to see whether there are improvements in model performance compared to the the observed streamflow.

1.7. Scope and Boundary

1.7.1. Scope

In this research, the satellite precipitation product will be assessed by statistical comparison with observed data and application in rainfall-runoff hydrological modelling to observe whether the SPP product is feasible to be used in the corresponding area. The newest Soil and Water Assessment Tool (SWAT) model called SWAT+ will be used. This latest model has been improved with more capability to simulate the actual processes and interactions in the hydrological model (Senent-Aparicio et al., 2021). This model will represent the hydrological processes of upstream Bengawan Solo catchment in the West side of Mount Lawu.

1.7.2. Boundaries

The study will be using calibrated SWAT+ model. For simplification, the model will not be recalibrated to fit the satellite precipitation and will stick to the actual calibrated models. Moreover, aiming to have a better representation of the actual conditions, the hydrological model will be simulated for the period from 2008 to 2020 which matches the observed precipitation and streamflow data in the location. Due to the limited availability and quality of the data, the observed rainfall is only collected from 12 rainfall and meteorology stations that spreads over the catchment. The modelling process will be divided into three periods starting with two years of warm-up period that will begin from 1 January 2008 to 31 December 2009. The calibration period is five years starting from 1 January 2010 to 31 December 2015. Lastly, the validation period from 1 January 2016 until 31 December 2020

2. Research Methods

2.1. Material

2.1.1. In-situ Data

For the research, some data from field observation is needed. Obviously, the precipitation data obtained from in-situ measurement stations is required as the reference for the comparison with the satellite precipitation product to determine the accuracy of the corresponding product. In this research, observed precipitation from 12 stations spread over the upstream of the Bengawan Solo catchment is used for the assessment. Overview of the stations can be seen in Table 1. However, for the modelling in a later stage, the dataset that is needed is not only precipitation. There is another dataset that is required from the in-situ measurement for the model's input such as temperature, wind speed and humidity. These data could only be obtained from meteorology stations. Among these 12 stations that were selected for the study, there are five meteorology stations that will be used. These meteorology stations are indicated with symbol (*) at the beginning of their name in Table 1. The other stations are considered as the rainfall stations.

Table 1. Stations overview

Station Name	Coordinate	Elevation	Data Type			
			Precipitation	Temperature	Humidity	Wind Speed
*Cengklik	7°31.08' S, 110° 43.8' E	138	✓	✓	✓	✓
*Kedunguling	7°56.46' S, 110° 50.52' E	158	✓	✓	✓	✓
*Ketro	7°22.68' S, 110° 53.94' E	105	✓	✓	✓	✓
*Ngancar	7°59.34' S, 110° 58.74' E	243	✓	✓	✓	✓
*Patihan	7°26.4' S, 110° 57.12' E	81	✓	✓	✓	✓
Bendosari	7°41.7' S, 110° 52.98' E	115	✓	-	-	-
Delingan	7°35.28' S, 110° 59.22' E	191	✓	-	-	-
Jumantono	7°40.02' S, 110° 0.72' E	343	✓	-	-	-
Kemuning	7°37.44' S, 112° 6.3' E	784	✓	-	-	-
Polokarto	7°37.74' S, 110° 53.76' E	119	✓	-	-	-
Sukoharjo	7°40.74' S, 110° 50.34' E	99	✓	-	-	-
Tawangmangu	7°39.96' S, 111° 7.32' E	1002	✓	-	-	-

As seen in Figure 2, there are stations that located inside and outside the study area. The reason to include the stations that is mainly to increase the number of stations that will be used for the comparison and for the input in modelling phase.

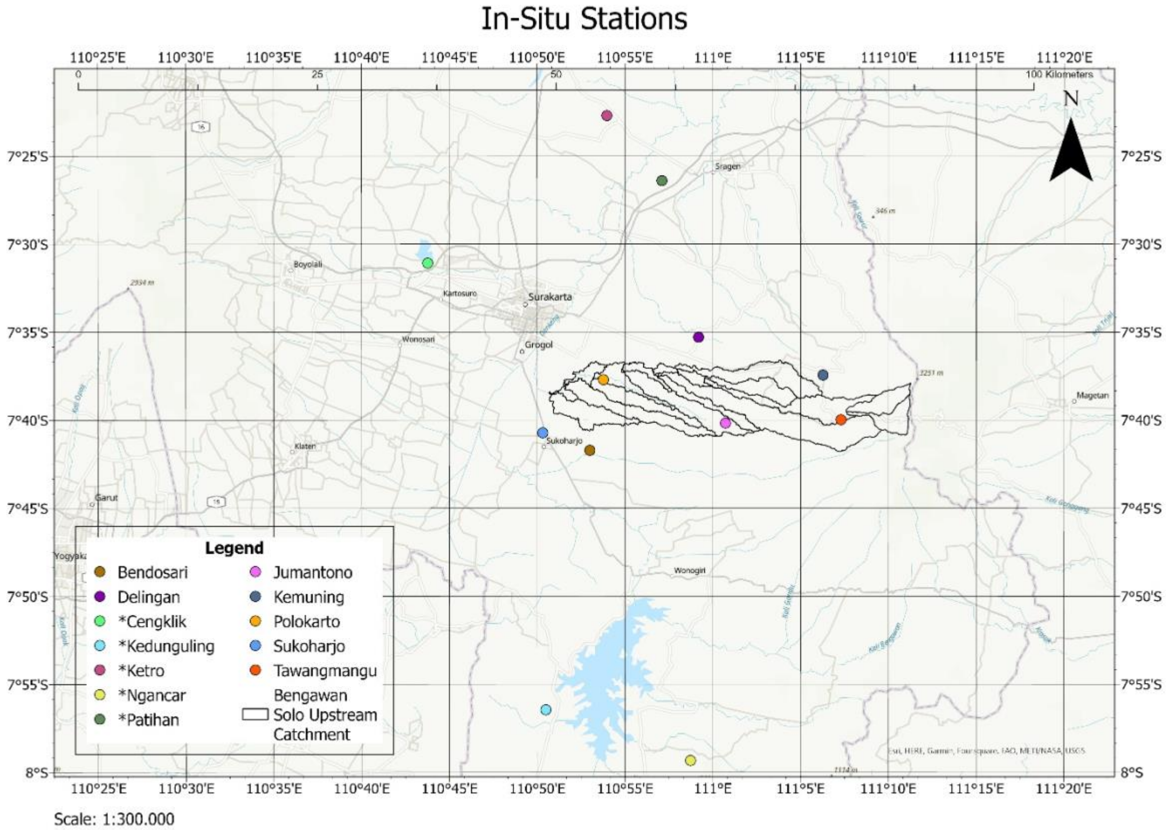

Figure 2. In-situ stations

2.1.2. Satellite precipitation products (SPPs)

Currently, the evaluation of satellite precipitation products in South-East Asia especially in Indonesia is rarely practiced. One of the satellite precipitation evaluations in Indonesia was performed by Rahmawati and Lubczynski (2018), where CMORPH25, CMORPH8, TRMM, and PERSIANN were assessed using a descriptive statistic to compare with the ground gauge data. The study was conducted on Bali Island which is located approximately 500 km east of this study area (Bengawan Solo Catchment). According to the results, CMORPH25 has relatively the lowest statistical bias compared to the other even though the accuracy is decreasing in the dry period. Referring to Table A. 1 and as assessed in the previous section, the CMORPH dataset provides rainfall data starting from December 2002 up until the present.

Another study was conducted by one of the researchers of the Indonesian Agency for Meteorological, Climatological and Geophysics (BMKG). BMKG is one of the most important Indonesian governmental institutions responsible for providing meteorological, climatological and geophysics data for the government and the public. Wati et al. (2022) analyzed eight satellite precipitation products by comparing them to the rain gauge that spread all over

Indonesia (mainly in Java) retrieved from BMKG observations and interpreted the results using several statistical indicators. It was found that MSWEPv2 is the most outstanding product among the others. MSWEPv2 has a significantly low bias in comparison with BMKG's rain gauge data. Moreover, according to Beck et al. (2017), MSWEPv2 shows a significantly better performance compared to the other 21 SPPs and it performs as the most accurate product for the tropical region. The temporal period availability for MSWEP also fits the intended period for this research which is available from 1979 until present.

For this research, the available satellite-based precipitation around the globe needs to be selected. In determining the relevant products, the criteria such as performance and spatial and temporal resolution will be inspected. The performance criterion refers to which satellite product is the best based on the accuracy for the study area which focuses on the South-East Asia region. Spatial and temporal resolution requirements identify the data availability for the desired location and period of the study. The required period for the data is starting from 2008 to 2020. From the literature that discussed before, CMOPRH and MSWEP have passed all of the criteria for this research. Therefore, considering the relevance of the satellite product for the study area, both the CMORPH and MSWEP dataset will be used for the research.

2.1.2.1. Climate Prediction Center Morphing Technique (CMORPH)

Climate Prediction Center Morphing Technique (CMORPH) is one of the satellite products that exists serving precipitation data since January 1998 until present. National Oceanic and Atmospheric Administration (NOAA) is the United States governmental agency that is responsible for serving this data (Precipitation - CMORPH CDR, 2023). This satellite product uses relatively low-frequency passive microwave (PMW) signals to estimate the precipitation on top of the cloud (Joyce et al., 2004). These precipitation data are then processed with a method called "morphing", where the precipitation data is interpolated using a time-weighted scale. The spatial resolution of each pixel of this data covers approximately 0,25 degrees lat/lon. The temporal resolution is ranging from every 30 minutes, hourly to daily. For this research, the daily time scale will be used for the comparison with the observed precipitation. As seen in Figure 3, the study area is only covered by two pixels. However, other pixels will also be used for the comparison with the other in-situ stations located outside the study area. This figure was using the CMOPRH precipitation data on 1 January 2010. The darker color of the pixel represents higher precipitation value on that date.

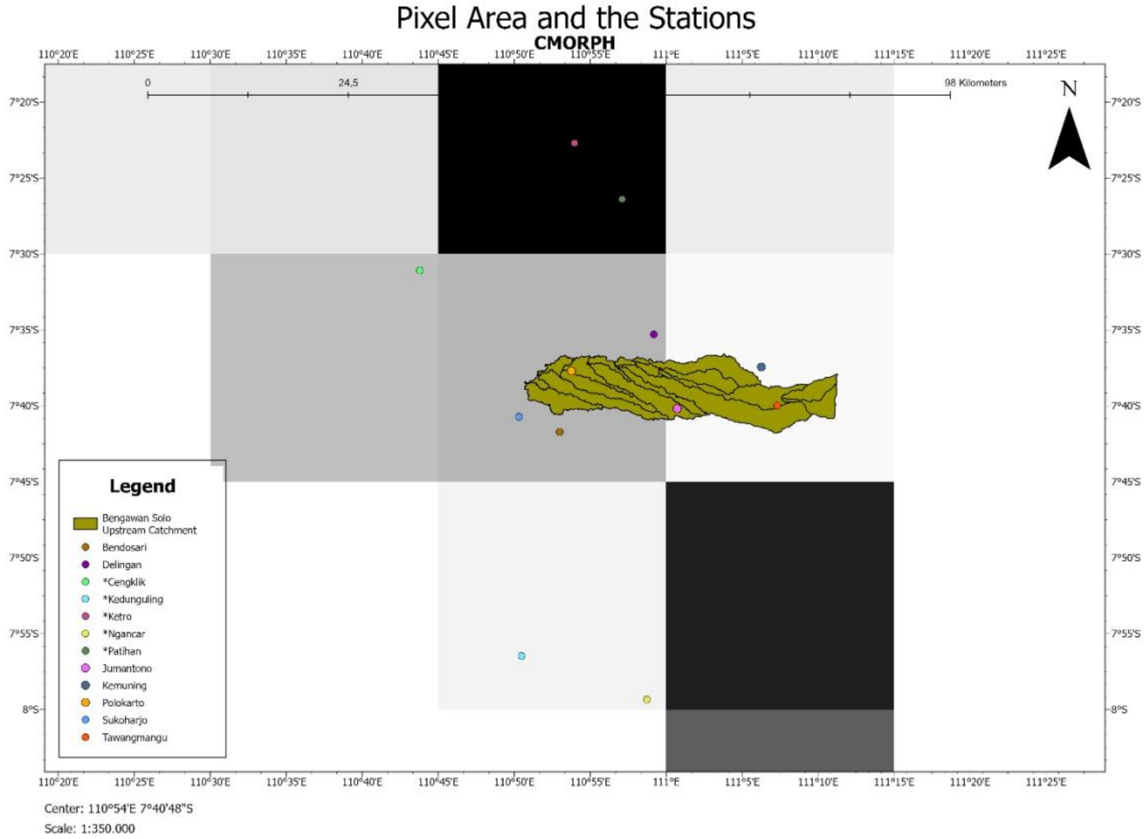

Figure 3. CMORPH pixels

2.1.2.2.Multi-Source Weighted Ensemble Precipitation (MSWEP)

MSWEP is one of the most advanced satellite precipitation products. The precipitation from this product is not only derived by the estimation from satellite sensors but also integrated with the data from gauges observation together with reanalysis data. As the results, the performance of this product is higher compared to other products. MSWEP was already tested by many researchers and has shown a higher performance compared to other products (Beck, Van Dijk, et al., 2017). This product serves the precipitation data from 1979 up until three hours from real-time or called near real-time (NRT). The spatial resolution of this product is 0,1 degrees or approximately 11 km by 11 km near the equator.

The MSWEP precipitation data is available and can be easily accessed through the GloH2O website (MSWEP - GLOH2O, 2023). However, permission is needed to clarify that there is no commercial purpose in using this data. Moreover, downloading the MSWEP data could only be executed by using a program called “rclone”. After the data is downloaded, the data is cropped according to the location of the study area. As seen in Figure 4, It was found that the MSWEP pixel is relatively small. As stated before, the pixel size of MSWEP is 0,1 degrees which is smaller if compared to the CMORPH's pixel with 0,25 degrees. With a smaller grid cell, MSWEP have a higher resolution and might lead to more accurate prediction compared to CMORPH satellite products.

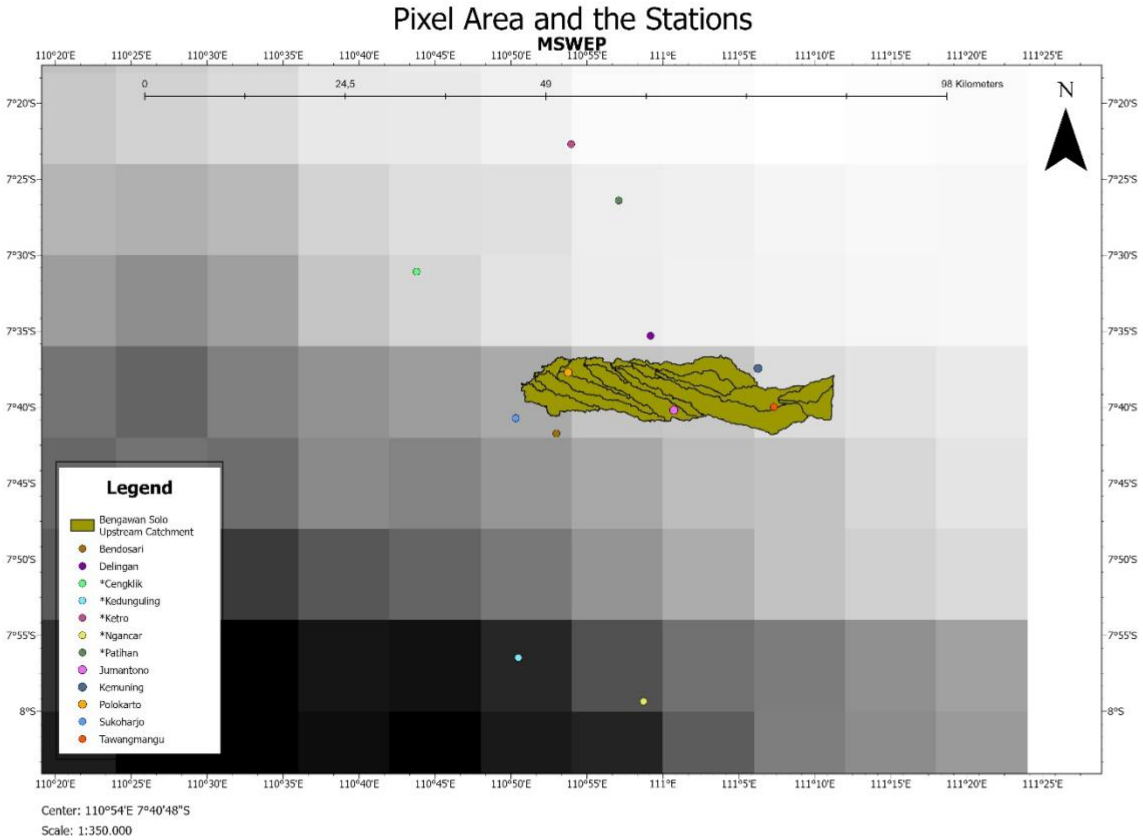

Figure 4. MSWEP pixels

2.2. Methods

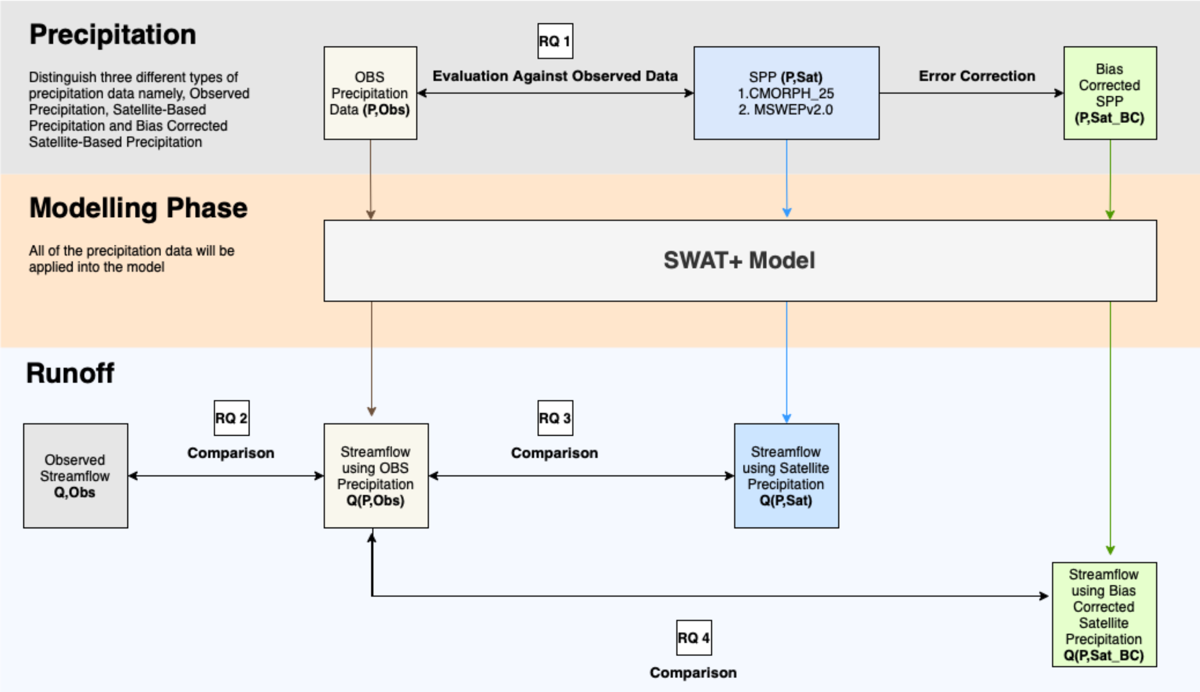

Figure 5. Proposed Research Methodology

As seen in Figure 5, the method will be conducted in a structured way starting from the pre-modelling phase to the post-modelling stage. Firstly, the precipitation retrieved from satellite data needs to be interpolated before the assessment. The interpolation method will be described in the next part. Table 2 explains the initials used in the flowchart.

Table 2. Initials In Flowchart

Name	Descriptions
OBS	Observed
P,Obs	Observed Precipitation
P,Sat	Satellite-Based Precipitation
P,Sat_BC	Bias-Corrected Satellite-Based Precipitation
Q,Obs	Observed streamflow
Q(P,Obs)	Simulated streamflow using observed precipitation
Q(P,Sat)	Simulated streamflow using satellite-based precipitation
Q(P,Sat_BC)	Simulated streamflow using bias-corrected satellite-based precipitation

2.2.1. Comparison of SPP Against Observed Precipitation

Corresponding to the first research question, the precipitation that will be used in the hydrological model will be assessed to find out whether satellite products predict accurate rainfall in the studied area. As mentioned in the previous section, the CMORPH25 and MSWEPv2.0 datasets will be used in the analysis. To assess the accuracy of the satellite precipitation product, observed precipitation data obtained from 12 rain stations in the catchment will be used as the reference for the testing. Firstly, the satellite-based precipitation data will be collected from the database according to location and desired temporal period as the observed precipitation from the ground stations. The period for the testing spans 12 years starting from 1 January 2008 up until 31 December 2020. As seen in Figure 3 and Figure 4, both satellite products have different pixel sizes. Each pixel has a different number of in-situ stations. There are pixels with only one in-situ station and there are pixels with more than one in-situ stations inside. Five pixels from CMORPH coverage and nine pixels from MSWEP coverage are numbered and taken for the following assessment. The list of numbered pixels and the corresponding in-situ stations located inside the pixels can be found in Table 3.

Table 3. List of SPP pixel and the corresponding in-situ stations

SPP	Pixel ID	Corresponding in-situ stations	Number of in-situ stations
CMORPH	CMORPH_1	iPatihan & iKetro	2
	CMORPH_2	iCengklik	1
	CMORPH_3	Delingan, Sukoharjo, Polokarto & Bendosari	4
	CMORPH_4	Tawangmangu, Jumantono & Kemuning	3
	CMORPH_5	iNgancar & iKedunguling	2
MSWEP	MSWEP_1	iKetro	1
	MSWEP_2	iPatihan	1
	MSWEP_3	iCengklik	1
	MSWEP_4	Delingan	1
	MSWEP_5	Sukoharjo, Polokarto & Bendosari	3
	MSWEP_6	Jumantono	1
	MSWEP_7	Tawangmangu & Kemuning	2
	MSWEP_8	iKedunguling	1
	MSWEP_9	iNgancar	1

To have a reliable and credible comparison between both satellite products against the observed precipitation, for the pixel that has more than one in-situ station inside the pixel, the daily monitored rainfall will be calculated using the average precipitation from all in-situ stations located inside the corresponding pixel per day. For example, the pixel CMORPH_3 in Table 3 has four stations inside the pixel. Therefore, the observed precipitation will be calculated using the average value from these four stations in daily time steps. After both observed and satellite precipitation data are matched with the same spatial and temporal resolutions, the next step is to assess the accuracy of the SPP.

According to a study conducted by Wang et al. (2020) about the evaluation of several SPP products, several indicators can be used for measuring the accuracy of the SPP such as Pearson correlation coefficient (CC), mean error (ME), root mean squared error (RMSE), percentage bias (PBIAS), probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI). Another study conducted by Sun et al. (2016) suggests that the SPP accuracy can be verified using systematic bias (BIAS), bias-adjusted root square mean error (aRMSE) and relative error (RE). They argue that BIAS is the simplest method to assessed while aRMSE is implemented to have a more accurate view because it eliminates the systematic error and leaves only the random error. In addition, mean absolute error (MAE) calculates the average of the absolute difference between observed and simulated data (Katiraie-Boroujerdy et al., 2013). According to a study that comparing the performance of RMSE and MAE indicators by Willmott and Matsuura (2005), it was concluded that the application of MAE indicators for measuring the model performance outperforms the RMSE. Therefore, considering the preciseness and simplification of the indicator, only two of the investigated equations will be used as listed below. Finally, a chart will be presented as a result to compare the accuracy. For all equations:

n is the total number of time steps (the number of the collected samples)
$P_{sat,i}$ is the satellite precipitation for every i
$P_{obs,i}$ is the observed precipitation for every i
i is the corresponding daily data

2.2.1.1. BIAS Indicators

The indicator is calculated by subtracting each observed data from each satellite precipitation and summing up all the differences then dividing by the number of days. The output is expressed in the same unit as precipitation $\left({}^{mm}/_{day}\right)$. For the BIAS indicators, zero is the optimal value that could range between negative infinity and positive infinity $(-\infty, +\infty)$. The formula is as follows:

Equation 1

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}(P_{sat,i} - P_{obs,i})$$

(Sun et al., 2016)

2.2.1.2. Mean Absolute Error

Almost the same as the BIAS Indicator, the Mean Absolute Error is calculated by summing up the differences between observed precipitation and satellite precipitation and then dividing by the total number of days. However, MAE is using absolute value of the differences. The output is expressed by precipitation units $\left({}^{mm}/_{day}\right)$.

Equation 2

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(P_{obs,i} - P_{sat,i})\right|$$

(Katiraie-Boroujerdy et al., 2013)

2.2.2. Modelling: Soil and Water Assessment Tool (SWAT+)

Aligning with the second research question, a hydrological model is needed and must be tested using the observed data as input before testing using the satellite precipitation data as the input. In this section, the model used in this research will be explained together with the modelling process and at the end, the evaluation procedure and the indicators will be described.

The soil and water assessment tool (SWAT) is a hydrological model created by the United States Department of Agriculture (USDA). This model is often used for evaluating the hydrological processes in specific locations by simulating hydrological, sediment and pollutants processes (Aloui et al., 2023). The SWAT+ model is an advanced version of the previous SWAT version. This version introduced several features such as integration with Geographic Information System (GIS) data and using land use or land cover in the model to have a more accurate simulation. The SWAT+ model can be implemented as a plugging in a GIS software interface called Quantum GIS (QGIS) which makes it easier to simulate the hydrological processes using GIS databases or shapefiles. In this project, the Quantum GIS version 3.28.6 (long-term released is used for the SWAT+ model).

The modelling process of SWAT+ is divided into four main steps. These processes start with delineating watersheds, creating hydrologic response units (HRUs) and inputting the meteorological data such as precipitation, temperature, humidity and wind speed. Lastly, the SWAT+ model is starting to simulate the hydrological processes and generate streamflow as a result.

In delineating the watershed, the model needs Digital Elevation Model (DEM) map to define and identify the elevation in the area and also the outlet points where the water flows out. The DEM maps for the study area were retrieved from the Indonesian Geospatial Information Agency or in Indonesian, a governmental organization responsible for providing GIS databases in Indonesia (DEMNAS, 2023). This DEM map is called DEMNAS which provides an elevation map with a spatial resolutions of 5 m. As seen in Figure 6, the DEMNAS data were downloaded and cropped according to the location of the study area.

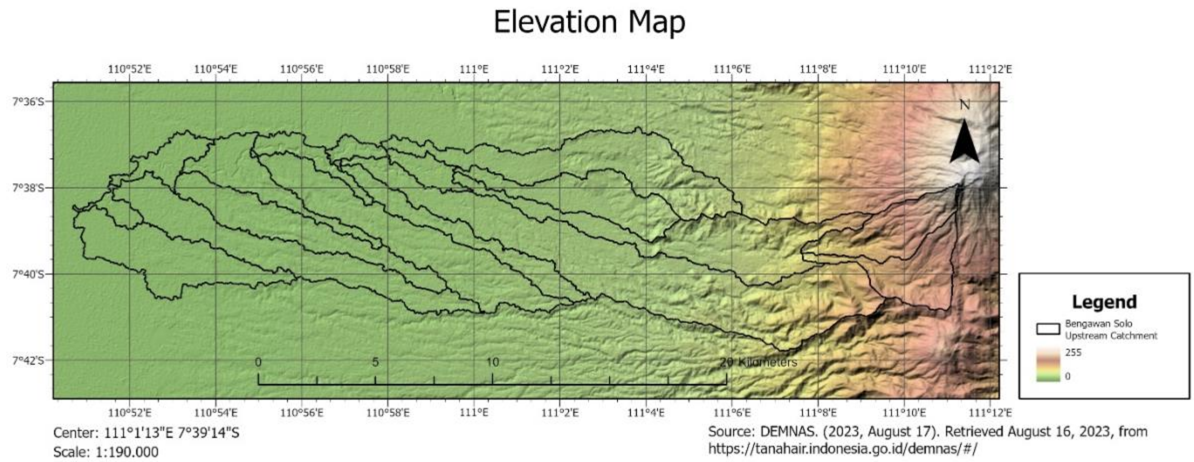

Figure 6. Elevation map

After the watershed is defined and delineated, the next step is to create the hydrologic response units (HRUs). The SWAT+ model will make spatial units for representing the areas that have similar hydrological characteristics within the watershed starting with the HRUs based on soil classification, land use and slope. In this stage, the data needed are soil classification map and land use map. Due to lack of soil data in Indonesia, the model uses the soil classification map produced by the Food and Agriculture Organization (FAO) of the United Nations. The FAO database provides the world’s soil classification map which is divided into several contingency maps based on the area (FAO/UNESCO Soil Map of the World, 2023). For the model, the Southeast Asia map is used. Similar to the DEM map described in the previous part, the soil map of Southeast Asia was also cropped according to the location of the study area. As seen in Figure 7, based on the FAO database, there are only four types of soils that exist around the upstream Bengawan Solo catchment and only three types inside the catchment.

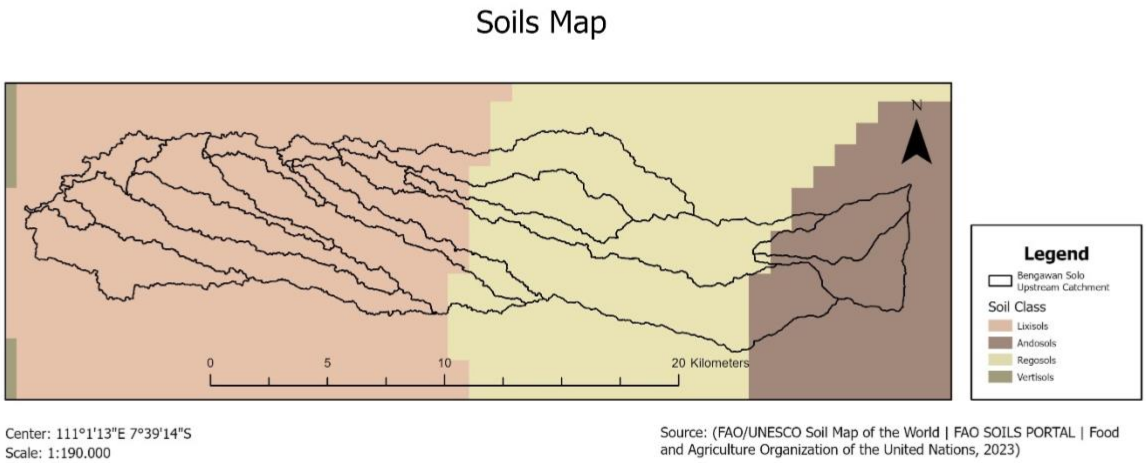

Figure 7. Soil map

The next step in creating the HRUs is inputting the land-use map. In this project, the land-use map was using the map provided by the University of Indonesia that was made based on field observations. As seen in Figure 8, there are nine types of land cover inside the study area.

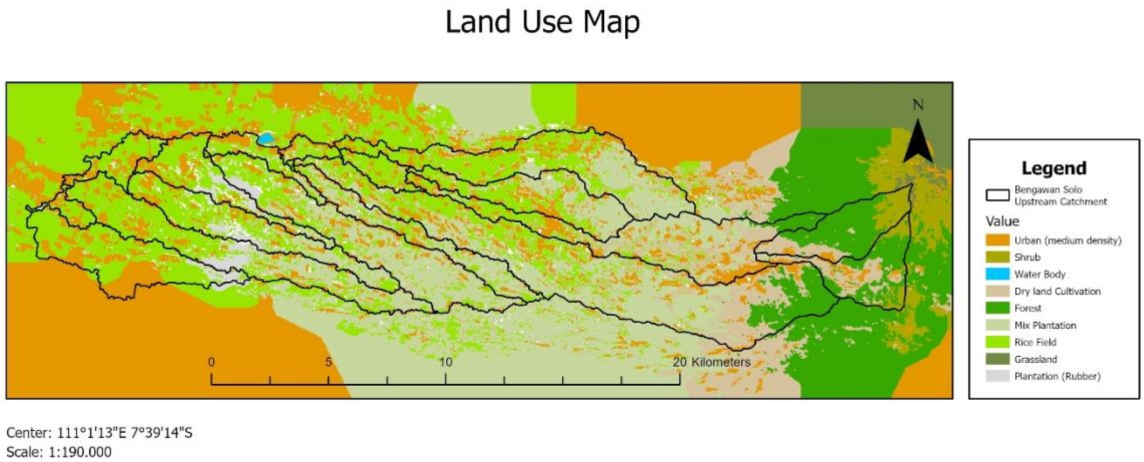

Figure 8. Land use map

The SWAT+ model identified 1876 HRUs, 79 water channels and 9 subbasins inside the study area which can be seen in Figure 9.

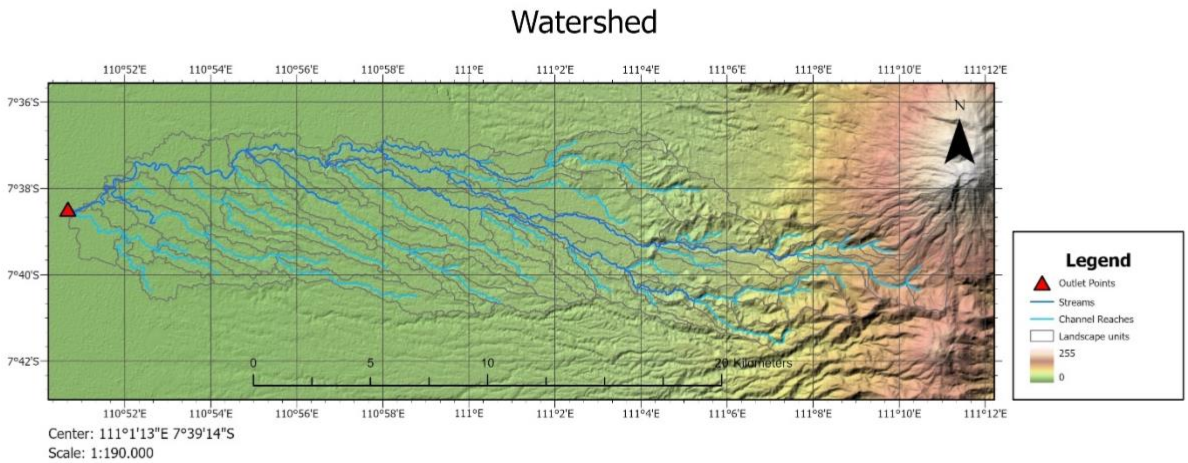

Figure 9. The watershed delineated by SWAT+ model

Finally, the last step before running the model is to input the weather data. As described in the previous section, the input needed is precipitation, humidity, temperature, and wind speed. For the precipitation, the input will be the data from both the satellite precipitation products and the observed data. Unlike the precipitation, the other meteorological data namely, humidity, temperature and wind speeds will be using the climatology data obtained from in-situ observation for all of the model scenarios.

2.2.3. Calibration parameters

In order to increase the performance of the model to simulate actual conditions, the model is calibrated using several parameters obtained from previous study from the team of University of Indonesia. These parameters are found to be the most sensitive parameters that will directly affect the model results. In SWAT+ model there are two types of calibration. The first one is the hard calibration which is the technique that normally used for calibrating model using time series data. The other one is called soft calibration which refers to the calibration that focused on the water balance components based on soft data (Chawanda, 2018). The soft calibration was introduced by the SWAT+ contributors aiming to complement the use of hard calibration that focused on discharge. However, in this research, the calibration is only deducted using hard calibration for simplification. As seen in Table 4, there are seven parameters that will be changed using absolute value (absval) or percentage changes (pctthg). The absolute value change means that the default value of the parameter will be changed to fixed value that inserted. The percentage change means changing the initial value by increasing or decreasing the value using percentage value that inserted. For example, the curve number conditions II (CN2) is the only parameter that will use percentage changes and as seen in Table 4, the percentage value that inserted to the model is -35,820 which refers to the initial value that will be decreased by 35,820 percent from the initial conditions. For the other parameters, fixed absolute values are applied. In later stage, these parameters will be applied to all models that run use satellite precipitation and observed precipitations.

Table 4. Calibration parameters

Parameters	Description	Units	Change Type	Applied change		
				Min	Max	Calibrated value
CN2.hru	Curve number conditions II	-	pctthg	35	95	-35,820
CN3_SWF.hru	Soil water factor for curve number III	-	absval	0	1	0,988
K.sol	Saturated hydraulic conductivity	mm h^{-1}	absval	0,0001	2000	18,204
LATQ_CO.hru	Lateral flow coefficient	-	absval	0	1	0,562
LAT_LEN.hru	Slope length for lateral subsurface flow	m	absval	1	150	6,465
PERCO.hru	Percolation coefficient	-	absval	0	1	0,451
ESCO.hru	Soil evaporation compensation coefficient	-	absval	0	1	0,015

2.2.4. Model testing and performance indicators

The simulated and the observed streamflow will be compared using the same method as proposed in the previous section. BIAS and MAE will be used to determine the performance of the model simulating the actual conditions. Additionally, there is another approach to evaluate the model performance that is widely applied for hydrological modelling called Nash-Sutcliffe Efficiency (NSE). The result of the Nash-Sutcliffe Efficiency is shown by a range starting from negative infinity to one. The closer the value to one, the more precise the model predicts the actual conditions. However, there are some issues regarding the suitability of NSE. Gupta et al. (2009) argue that using NSE might lead to an overestimation of the model while using a high precipitation value because of the use of the observed mean as the reference. They then suggest a new approach called Kling-Gupta Efficiency (KGE) which is a derived formula from the Nash-Sutcliffe Efficiency (NSE). However, the NSE is still widely used by many researchers. Therefore, for simplification and comparability with other research, Nash-Sutcliffe Efficiency might still be a reliable indicator for this model evaluation and will be applied in the study. The NSE value is ranged between minus infinity to one as the most optimal value ($-\infty < NSE < 1$). According to Schaefli and Gupta (2007), the model that obtained an NSE value below zero indicates that the model's predictions are worse compared to the observed data. NSE value above the zero and close to one can be considered acceptable. The closer the NSE value to one is indicating good fit between the generated streamflow compared to the observed data. Finally, the comparison between the simulated and observed discharge will be shown using hydrograph to have a better understanding of the results.

Equation 3

$$NS = 1 - \frac{\sum_{i=1}^{n}(Q_{S,i} - Q_{O,i})^2}{\sum_{i=1}^{n}(Q_{O,i} - \mu_0)^2}$$

(Nash & Sutcliffe, 1970)

Where,

n is the total number of time steps (the number of the collected samples)

$Q_{s,i}$ is the simulated streamflow from observed precipitation for every i

$Q_{O,i}$ is the observed streamflow for every i

μ_0 is the average of the observed streamflow

2.2.5. Performance of the Hydrological Model Using SPP

After the model is validated, the next step is to assess whether the satellite product could be used as input for the model. The assessment will use both generated streamflow from observed precipitation and satellite precipitation where the generated streamflow obtained using observed precipitation will be used as the reference. The performance indicators are the same as explained in the previous sections namely, BIAS, MAE, and NSE.

2.2.6. Bias Correction

As described in the introduction, the precipitation obtained from satellite products does not directly represent the actual precipitation on the ground. The satellite precipitation is derived from an observation on top of the cloud using satellite sensors and estimated using empirical formula. Due to this process, the precipitation prediction from satellite data might contain some errors or biases. Aiming to increase the accuracy of the satellite precipitation for using it in the hydrological model, bias-correction method is needed to improve the quality of the satellite precipitation data. The aim of conducting bias correction is mainly to improve the model's performance that uses satellite precipitation. The improvement can be tested by using the indicators described in section 2.2.1. Firstly, the bias-corrected satellite precipitation will be evaluated against the observed precipitation from in-situ measurements. Thereafter, the bias-corrected precipitation will be applied to the calibrated model. The streamflow output from this model will then be evaluated against the streamflow generated by the calibrated model that uses the observed precipitation as the input.

There are several methods to reduce the bias in satellite data. As investigated by Ghimire et al. (2018), correction methods can be grouped into three categories according to the degree of the correction. The first example is delta change and linear scaling where the mean of the modelled data (satellite precipitation) is corrected according to observed data. The second category is the power transformation method which was found to be the most straightforward method for correcting the biases. And the last one is the quantile mapping method. This method evaluates the empirical probability function of both the modelled and observed precipitation then converts the modelled data using the inverse of the cumulative distribution function (CDF). In this project, the temporal resolution for the modelling is looking at the daily data which might have a high variability. In a study conducted by Enayati et al. (2020), it was found that the quantile mapping approach shows a good performance in correcting satellite precipitation data. Therefore, quantile mapping bias correction will be conducted in this project. The formula for quantile mapping is as follows:

Equation 4

$$Q = F_Y^{-1}(F_{\bar{F}}(\bar{F}))$$

(Enayati et al., 2020)

Where,

Q is the bias-corrected value.

F_Y^{-1} is the inverse CDF or the quantile function.

$F_{\bar{F}}$ is the CDF of the modelled precipitation $\bar{F}$.

According to Panjwani et al. (2020), the quantile mapping technique could be conducted in R programming using the Qmap package called "fitQmapQUANT". In this package, the observed and satellite precipitation will be taken as the input. This package will directly process the modelled precipitation using the quantile mapping approach. The output will be the bias-corrected precipitation that will be compared in further steps.

3. Results

3.1. Performance of SPPs for daily precipitation

One way to check the performance of each SPP is by comparing the indicators (BIAS and MAE) that have been described in the previous section. Consequently, both SPPs were compared with the observed precipitation. The comparison was initially conducted per pixel against the precipitation data from corresponding in-situ stations. However, the comparison is not only comparing one pixel but also comparing the combined pixels with observed precipitation from all 12 in-situ stations. The daily time-step starting from 1 January 2008 until 31 December 2020 was taken for the testing. The results of the comparison can be found in Table 5. Due to different pixel sizes and different in-situ stations that were taken as the reference for the comparison, CMORPH and MSWEP could not be directly compared pixel to pixel. The only pixels that can be compared side by side are CMORP_2 and MSWEP_3 because the in-situ station that is taken as the reference is the same (*Cengklik).

Generally observing the BIAS indicators, it can be identified that the CMORPH SPP seems to overestimate the daily precipitation in the study area whereas the MSWEP SPP seems to underestimate the precipitation data. This is indicated with the BIAS index for CMORPH that mostly showing positive values, except for the CMORPH pixel number 5, where a negative BIAS value was observed. This means that CMOPRH underestimates the precipitation in this area. On the other hand, the MSWEP SPP seems to underestimate the precipitation because eleven out of twelve MSWEP pixels are showing negative values for the BIAS indicator. For the CMORPH SPP, the most optimal BIAS value was observed in the pixel named CMORPH_2, which has BIAS value of 0.28 mm/day. However, the combined data of all five pixels shows a better performance with a BIAS value of 0.14 mm/day compared to single pixel comparison from CMORPH SPP. On the contrary, MSWEP SPP performance is even better even though it was underestimated. Referring to the BIAS indicator, among the nine pixels that are compared with the observed precipitation, eight pixels were underestimate the actual precipitation. Only pixel MSWEP_6 that slightly overestimate the precipitation with a BIAS value of 0.15 mm/day. The most optimal value of BIAS from the MSWEP SPP is observed on pixel MSWEP_5 with 0.04 mm/day close to zero. This is indicating MSWEP SPP is quite precise in generating precipitation compared to CMORPH SPP.

The mean absolute error (MAE) indicates the average magnitude of error from the corresponding product. The closer the MAE value to zero, the more accurate the prediction estimated by the products. CMORPH SPP has an MAE ranging between 6.26 mm/day to 10.15 mm/day. On the contrary, MSWEP SPP has a slightly lower range of MAE values, ranging between 5.10 mm/day to 8.43 mm/day. This indicates that the MSWEP SPP is producing a lower error compared to the CMORPH SPP. It was observed that among these two SPPs, the highest MAE value was found in the pixel CMORPH_2 with 10.15 mm/day. The lowest MAE was observed in pixel MSWEP_5 with 5.10 mm/day. Moreover, the pixel MSWEP_5 that represents three in-situ stations also shows the most optimal BIAS value compared to other MSWEP and CMORPH pixels with a value of -0.04 mm/day.

For the comparison between combined all pixels and all 12 in-situ stations, the BIAS for CMORPH is observed lower than the BIAS of MSWEP. On the other hand, the MAE of the MSWEP has a slightly lower value compared to CMORPH. Therefore, from the combined data, it cannot be concluded which SPP performs better. However, generally observing the indicators, MSWEP have a more accurate result. This was indicated by the number of pixels that represented the in-situ stations.

Table 5. Result of the SPPs assessment

Pixel ID	Corresponding in-situ station	Number of in-situ stations	BIAS (mm/day)	MAE (mm/day)
CMORP_1	iPatihan & iKetro	2	1.58	8
CMORP_2	iCengklik	1	0.28	10.15
CMORP_3	Delingan, Sukoharjo, Polokarto & Bendosari	4	1.39	6.81
CMORP_4	Tawangmangu, Jumantono & Kemuning	3	1.58	7.88
CMORP_5	iNgancar & iKedunguling	2	-0.99	6.26
Combined	All 12 stations	12	0.14	7.82
MSWEP_1	iKetro	1	-0.19	6.70
MSWEP_2	iPatihan	1	-0.67	8.02
MSWEP_3	iCengklik	1	-0.96	8.43
MSWEP_4	Delingan	1	-0.16	7
MSWEP_5	Sukoharjo, Polokarto & Bendosari	3	-0.04	5.10
MSWEP_6	Jumantono	1	0.15	7.87
MSWEP_7	Tawangmangu & Kemuning	2	-1.68	7.36
MSWEP_8	iKedunguling	1	-0.10	7.81
MSWEP_9	iNgancar	1	-0.37	5.84
Combined	All 12 stations	12	-0.45	7.13

3.2. Performance of the SWAT+ Model in the study area

In this section, the results generated by the SWAT+ model will be presented. Initially, the model results obtained with the observed precipitation will be compared with the reference streamflow (Q,Obs) gathered from observations at the outlet of the catchment (upstream Bengawan Solo catchment). The comparison will go through several scenarios starting with the uncalibrated model, then distinguish the calibration and validation period to have a better perspective of the model performance. The indicators used for the assessment are introduced in previous section namely, Nash-Sutcliffe Efficiency (NSE) together with the BIAS and MAE. The NSE will act as the main indicator that measures the model's performance.

Firstly, the model is running using the observed precipitation from 12 in-situ stations (P,Obs) for the uncalibrated period starting from 1 January 2010 up until 31 December 2020. As seen in Table 6, the NSE indicator for the uncalibrated model was 0.21 which can be considered not satisfactory. The BIAS indicator is showing a negative value which means that the model underestimates the streamflow compared to the observed streamflow. Figure 10 shows the hydrograph between the simulated streamflow and observed streamflow before calibration. After the calibration, as seen in Figure 11, the performance of the model is much improved with NSE value of 0.59 during the calibration period. The BIAS and MAE indicators during calibration period are also improved from -0.85 m^3/s to 0.05 m^3/s and 7.07 m^3/s to 4.27 m^3/s respectively. The BIAS indicator shows the model is no more underestimating the streamflow but slightly overestimating it. For the validation period (1 January 2016 until 31 December 2020) it was monitored that NSE is decreasing compared to the calibration period (0.59 to 0.47) but still improving significantly compared to the uncalibrated model results. This indicates that the calibration is indeed affecting the model's performance outstandingly and is vital to be conducted.

Table 6. Model performance using observed precipitation.

Reference	Period	Scenario	Model Output Q,P_Obs NSE	BIAS (m^3/s)	MAE (m^3/s)
Q,Obs	10 years (2010 – 2020)	Uncalibrated	0.21	-0.85	7.07
	5 years (2010 – 2015)	Calibration Period	0.59	0.05	4.27
	5 years (2010 – 2015)	Validation Period	0.47	-0.59	6.19

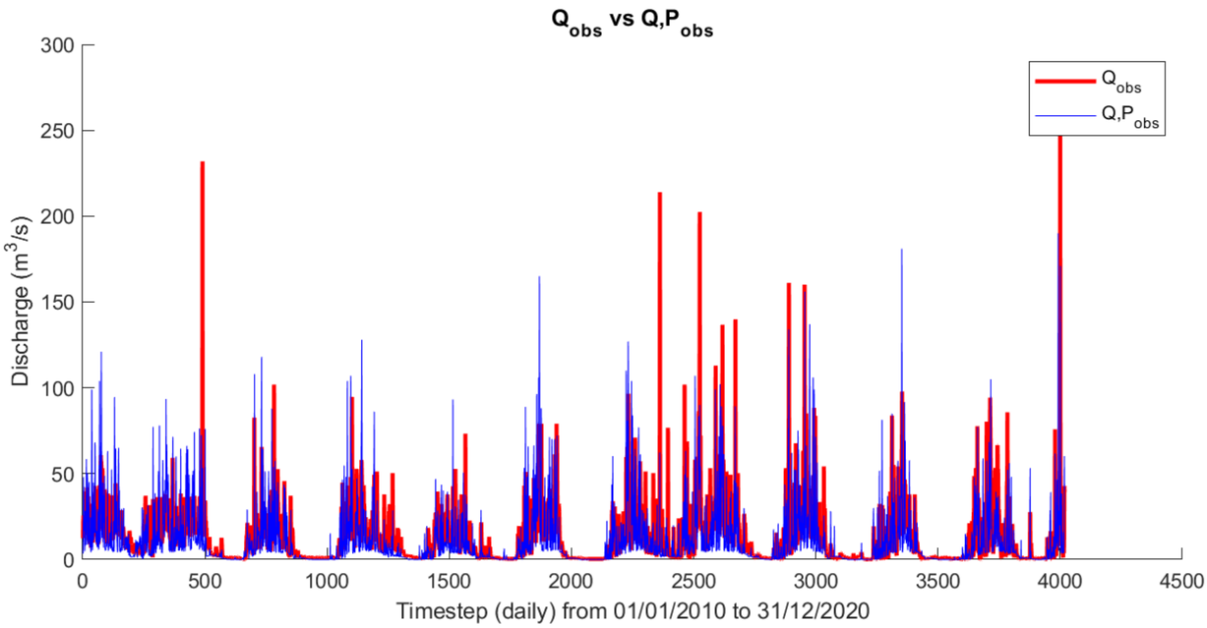

Figure 10. Observed and simulated streamflow using observed precipitation before calibration

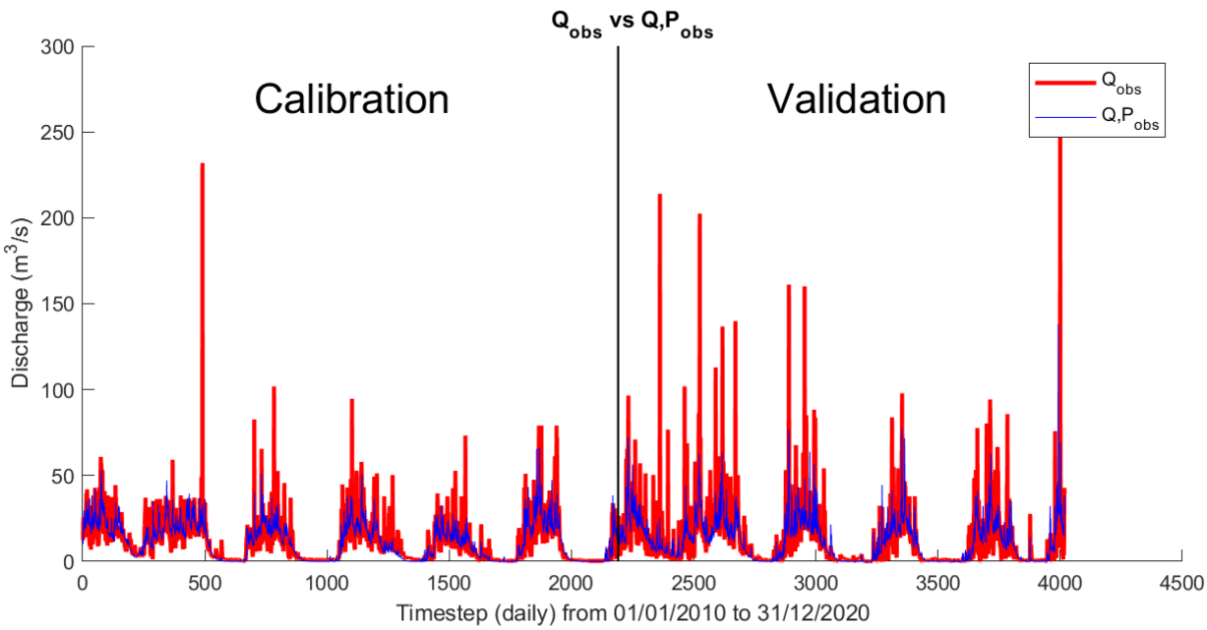

Figure 11. Observed and simulated streamflow using observed precipitation after calibration

3.3. Performance of SWAT+ model using satellite precipitation products

After the SWAT+ model is validated with the observed data, this model is used for testing the SPPs. In this term, the precipitation input is using the five pixels from CMORPH and nine pixels from MSWEP which was the same as the pixels that were used for the comparison with the in-situ stations assessed before. These pixels are including the pixels located exactly on the study area and also the pixels that located surrounding the study area. The reason of using the pixels located surrounding the study area will be explained in the discussion sections. The SWAT+ model used in this stage is calibrated using the parameters that obtained in the previous sections when running the observed precipitation. Firstly, the simulated streamflow using both SPPs will be compared with the observed streamflow. Then, the simulated streamflow using SPPs will also be compared with the simulated streamflow that use observed precipitation as the input.

3.3.1. Comparison with observed streamflow

Initially, CMORPH and MSWEP SPPs are used as the input for the calibrated SWAT+ model. Then the simulated streamflow using these SPPs are compared with observed streamflow. Figure 12 and Figure 13 shows the hydrograph of the results. As seen in Table 7, it was found that the NSE value for the streamflow generated using CMORPH data is 0.31 during the calibration period and increasing on validation period with NSE of 0.35. From the BIAS indicator, it was observed still underestimate the observed streamflow with value of -2.16 m^3/s on the calibration period. However, the BIAS is improving during the validation period with value of -1.49 m^3/s. The MAE was observed to be really high means that the streamflow generated by CMORPH precipitation (Q,P_Sat_CMORPH) contains a lot of errors compared to the observed streamflow (Q,P_Obs). For the streamflow generated using MSWEP data (Q,P_Sat_MSWEP), the NSE is 0.51 during the calibration period which is significantly higher compared to the streamflow that used CMORPH SPP. However, during the validation period, the NSE for model using MSWEP SPP is decreasing to 0.38. The BIAS of the streamflow using MSWEP precipitation is observed still below zero for both calibration and validation periods. However, the MAE for streamflow using MSWEP is ranging between 4.65 m^3/s to 6.55 m^3/s which is lower than the MAE range of the streamflow using CMORPH that ranging between 5.46 m^3/s to 7.33 m^3/s. This shows that streamflow simulated using MSWEP SPP is producing lower error than the streamflow simulated using CMORPH SPP.

From the BIAS indicators, it was shown that the streamflow generated using both products still underestimated the actual streamflow because the BIAS value below zero for all scenarios. Furthermore, in comparison with the observed streamflow as the reference (Q,Obs), the NSE and MAE of the streamflow generated by the model using MSWEP precipitation outperforms the model that uses CMORPH precipitation. Therefore, generally observing the performance of the model using SPPs, it can be indicated that MSWEP has a better performance in the SWAT+ model.

Table 7. Model's performance using SPPs.

Reference	Scenario	Model Output					
		Q,P_Sat_CMORP			Q,P_Sat_MSWEP		
		NSE	BIAS (m^3/s)	MAE (m^3/s)	NSE	BIAS (m^3/s)	MAE (m^3/s)
Q,Obs	Calibration Period	0.33	-2.16	5.46	0.51	-0.87	4.65
	Validation Period	0.35	-1.49	7.33	0.38	-3.29	6.55

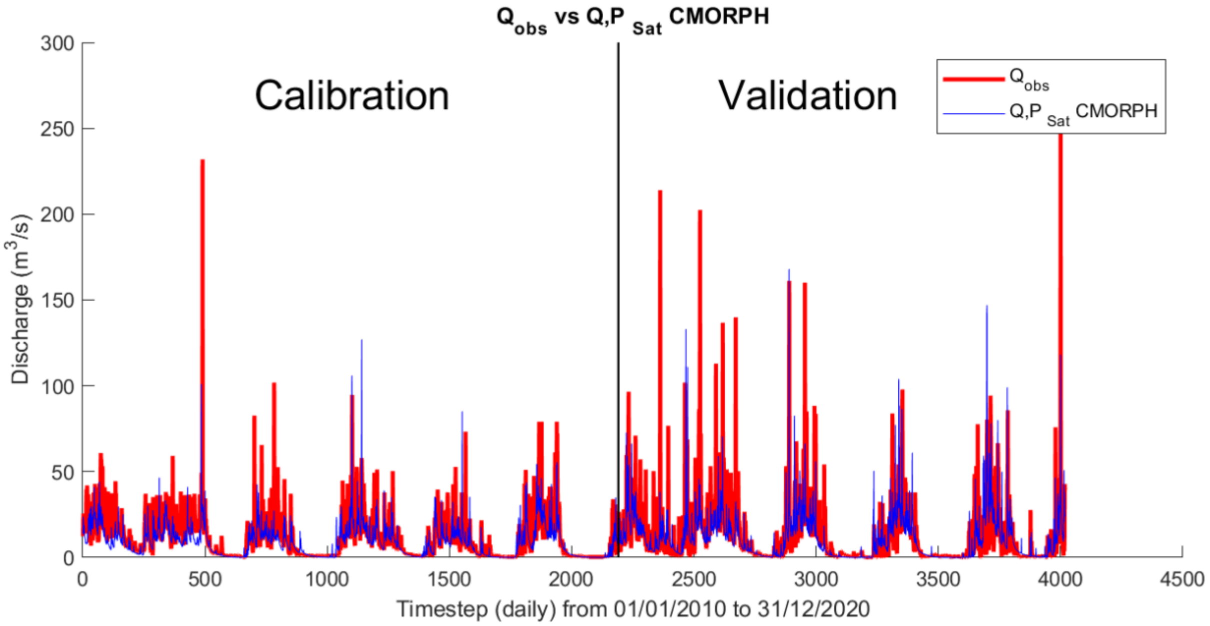

Figure 12. Observed and simulated streamflow using CMORPH SPP

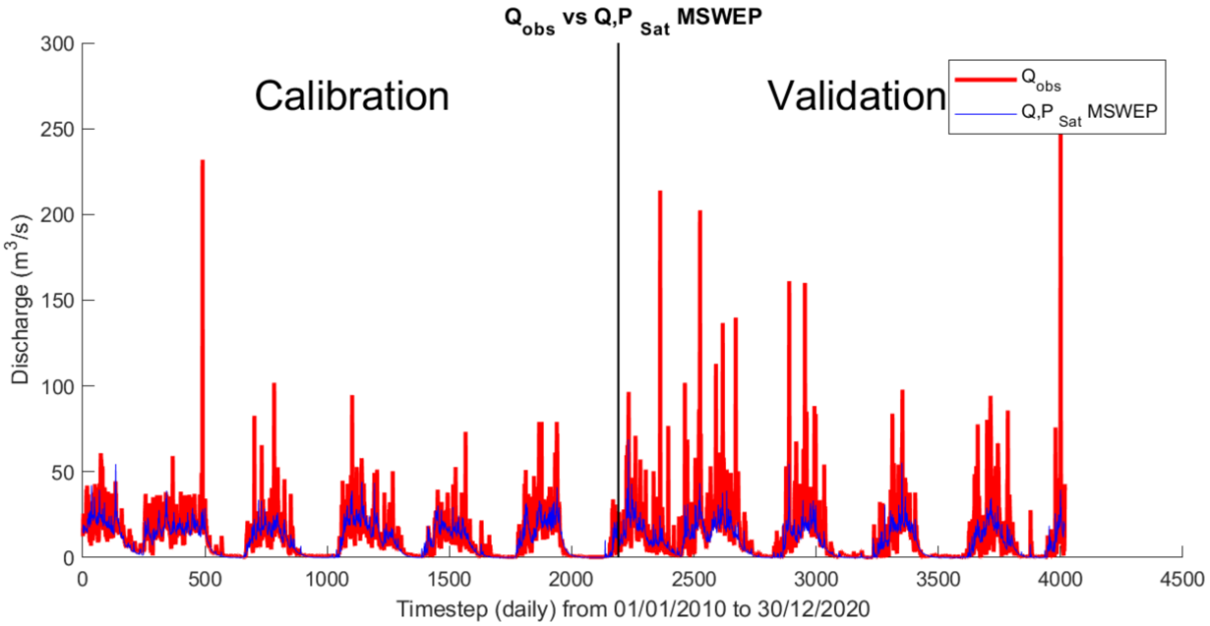

Figure 13. Observed and simulated streamflow using MSWEP SPP

3.3.2. Comparison with streamflow generated using in-situ precipitation

In this section, the streamflow generated using SPPs (Q,P_Sat_CMORPH & Q,P_Sat_MSWEP) was tested against the streamflow generated using observed precipitation (Q_P_Obs). As seen in Table 8, the MSWEP SPP is showing an outstanding result compared to the CMORPH SPP with NSE value of 0.75 that obtained during calibration period while CMORPH could only reach 0.42. The BIAS and MAE of streamflow using MSWEP SPP also shows lower values compared to the streamflow using CMORPH SPP. This could indicate that the streamflow generated using MSWEP precipitation is much closer to the streamflow generated using observed precipitation. Moreover, as observed in Figure 14, the streamflow generated using CMORPH SPP has more errors compared to the streamflow using MSWEP SPP in Figure 15.

Table 8. Results of comparison against the streamflow generated using observed precipitation

Reference	Scenario	Model Output					
		Q,P_CMORPH			Q,P_Sat_MSWEP		
		NSE	BIAS (m^3/s)	MAE (m^3/s)	NSE	BIAS (m^3/s)	MAE (m^3/s)
Q,P_Obs	Calibration Period	0.42	-2.20	4.97	0.75	-0.91	3.21
	Validation Period	0.27	-0.90	5.44	0.68	-2.71	3.83

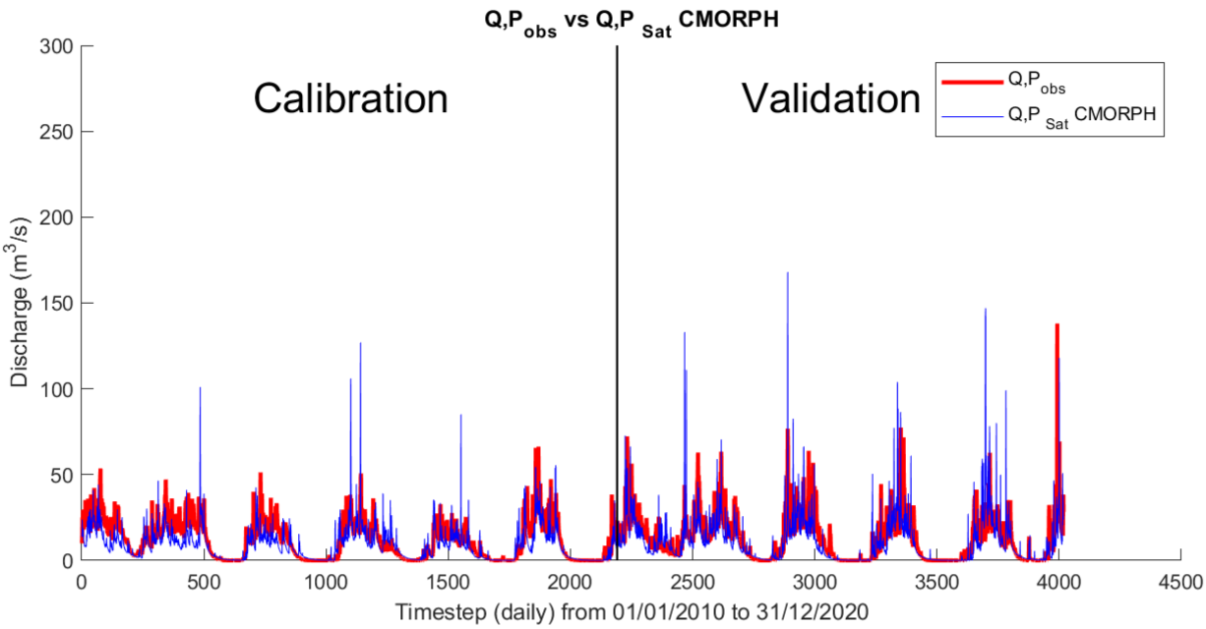

Figure 14. Simulated streamflow using observed precipitation and CMORPH SPP

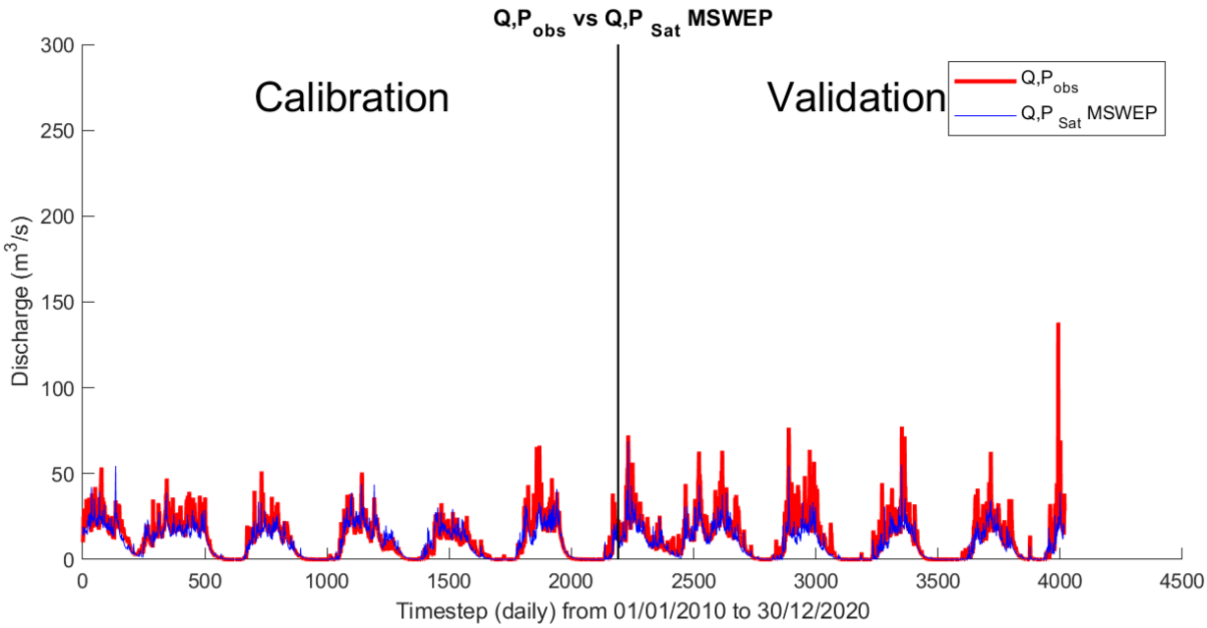

Figure 15. Simulate streamflow using observed precipitation and MSWEP SPP

3.4. Performance of the bias corrected SPPs

According to the assessment conducted in the previous section, the performance of the MSWEP satellite precipitation products especially in hydrological modelling, outperformed the CMOPRH satellite products. Due to this reason, the bias correction for the precipitation data is applied only for the MSWEP product. The bias-correction technique used was called Quantile Mapping where the selected satellite precipitation product (P,Sat_MSWEP) will be corrected using the in-situ precipitation (P,Obs) as the reference. The correction period was 12 years, starting from 1 January 2008 to 30 December 2020 using the combined data of nine pixels. The date 31 December 2020 was not included because MSWEP does not have the record for this period. For the observed precipitation data, the average value of daily precipitation from in-situ stations are used for matching the MSWEP pixels that contains more than one in-situ stations inside the corresponding pixels. After the bias correction is conducted for MSWEP datasets, the bias-corrected data will be compared against the observed precipitation using the same indicator namely BIAS and MAE. After the evaluation against the observed precipitation, the bias-corrected precipitation will be applied to the calibrated SWAT+ to assess the performance of this precipitation in generating the streamflow.

3.4.1. Evaluation with in-situ precipitation

As seen in Table 9, the column called 'Initial' refers to the performance of MSWEP precipitation products against the observed precipitation before the bias correction. Next to this column is the performance of the MSWEP SPP after the bias correction. For the combined pixels, it was observed that the bias correction shows an improvement in the BIAS indicator from -0.45 mm/day to 0.02 mm/day which shows MSWEP not underestimate the observed precipitation anymore. However, the MAE for the combined data was rather increasing from 7.13 mm/day to 7.98 mm/day. For the aggregated comparison per pixel, the BIAS is not improving for all the pixels. Only five out of nine pixels showed improvement in the BIAS indicator. This could be the impact of using the combination of all-stations that was used in this quantile mapping correction where the distribution function that will be applied for the correction was obtained from the combination of these stations. The distribution function of each in-situ station might differ from one another. For the MAE of the aggregated pixels, it was observed that the MAE values were increasing for all pixels which indicates the bias-corrected data containing higher error compared to the initial data.

Table 9. The results of bias corrected MSWEP SPP against the observed precipitation

Pixel ID	Corresponding in-situ station	Number of in-situ station	Initial		Bias-corrected	
			BIAS (mm/day)	MAE (mm/day)	BIAS (mm/day)	MAE (mm/day)
MSWEP_1	iKetro	1	-0.19	6.7	-0.14	7.01
MSWEP_2	iPatihan	1	-0.67	8.02	-0.49	8.59
MSWEP_3	iCengklik	1	-0.96	8.43	-0.99	8.96
MSWEP_4	Delingan	1	-0.16	7	0.06	7.48
MSWEP_5	Sukoharjo, Polokarto & Bendosari	3	-0.04	5.1	0.07	8.84
MSWEP_6	Jumantono	1	0.15	7.87	0.91	9.52
MSWEP_7	Tawangmangu & Kemuning	2	-1.68	7.36	0.12	9.52
MSWEP_8	iKedunguling	1	-0.1	7.81	0.74	9.17
MSWEP_9	iNgancar	1	-0.37	5.84	0.01	6.17
Combined	All 12 stations	12	-0.45	7.13	0.02	7.98

3.4.2. Performance in SWAT+ model

Right after the comparison with the observed precipitation, this bias corrected MSWEP precipitation was used for the input of the SWAT+ model. As the results of this model, the streamflow (Q,P_Sat_Bias_Corrected) was compared with both observed streamflow (Q,Obs) and the streamflow generated by the model using in-situ precipitation (Q,P_Obs). The performance of this model was also compared to the performance of the model before the bias correction obtained in the previous section.

In the evaluation using the observed streamflow as the reference, as identified in Table 10 and Figure 16, the performance of the model using the bias corrected MSWEP is not satisfactory enough and rather decreasing. During the calibration period, the NSE value was dropped from initially 0.51 to 0.26. The MAE value was also increasing from 4.65 m^3/s to 5.88 m^3/s. However, the only improvement was observed during the validation periods for BIAS indicator from -3.29 m^3/s to -1.26 m^3/s.

For the evaluation with the streamflow generated using observed precipitation, as observed in Figure 17, a similar path was observed where improvement was only on BIAS during the validation period from -2.71 m^3/s to -0.67 m^3/s. For the NSE and MAE indicators, no improvements were observed for all scenarios. This could be due to the calibration process that using the parameters obtained using observed precipitations. A recalibration process needs to be conducted after the bias correction. Both Figure 16 and Figure 17, shows that the streamflow generated using bias corrected precipitation yield more errors compared to the streamflow in Figure 13 and Figure 15 that use MSWEP SPP before the bias correction.

Table 10. Performance of the model using bias corrected MSWEP precipitation

Reference	Scenario	Model Output					
		Q,P_Sat_MSWEP			Q,P_Sat_Bias_Corrected		
		NSE	BIAS (m^3/s)	MAE (m^3/s)	NSE	BIAS (m^3/s)	MAE (m^3/s)
Q,Obs	Calibration Period	0.51	-0.87	4.65	0.26	1.28	5.88
	Validation Period	0.38	-3.29	6.55	0.35	-1.26	7.04
Q,P_Obs	Calibration Period	0.75	-0.91	3.21	0.33	1.23	4.51
	Validation Period	0.68	-2.71	3.83	0.46	-0.67	4.43

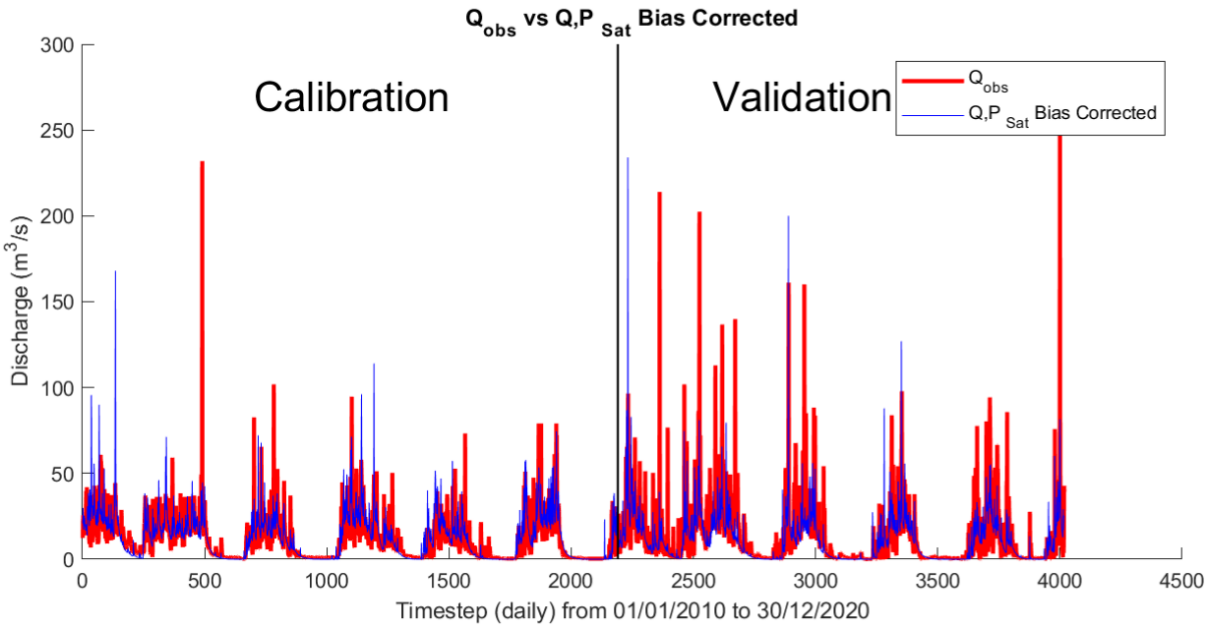

Figure 16. Observed and simulated streamflow using bias corrected precipitation

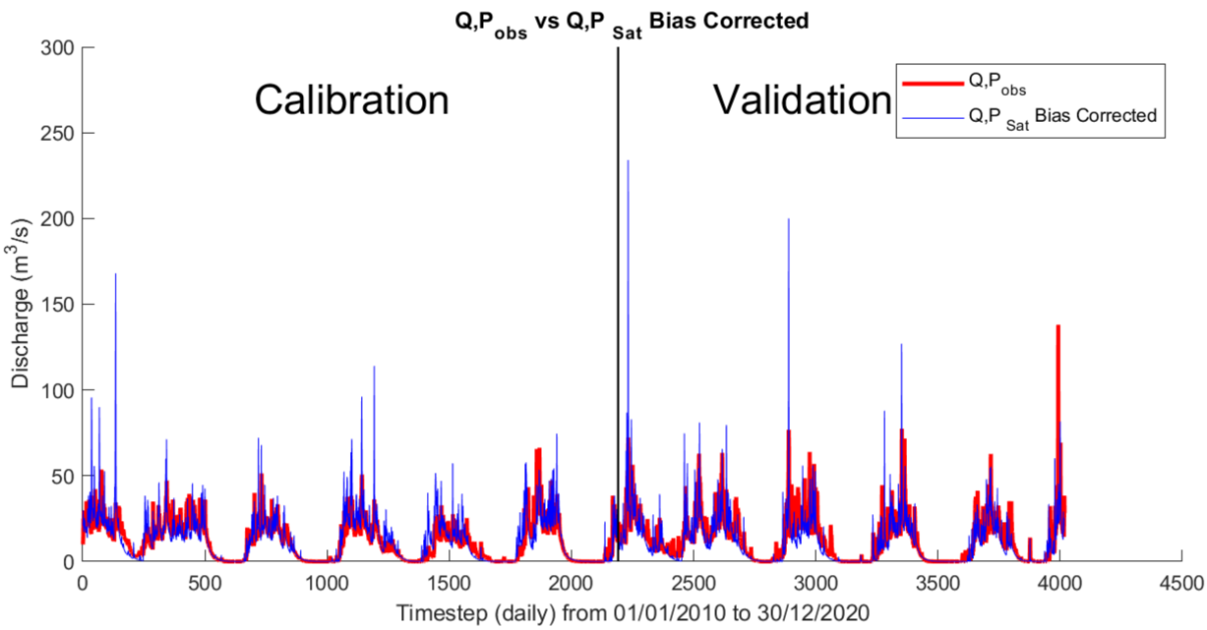

Figure 17. Simulated streamflow using observed precipitation and bias corrected precipitation

4. Discussion

This study was conducted to investigate the performance of the satellite precipitation products (SPPs) in the application of hydrological modelling. The main objective is to support the research relating to the application of satellite precipitation in hydrological modelling. This study is also aimed to overcome the complexity and data scarcity when using in-situ measurements for obtaining precipitation data. However, there are several limitations and key findings that were obtained during the research. Moreover, the results of the research will also be explained in comparison to the literature discussed in introduction chapter. Together, these findings will be explained in this chapter.

4.1. Limitations

During the study, there are several limitations that could not be avoided. One of the limitations is regarding the observed data availability in study area. Even though one of the objectives is to overcome the data scarcity in the study area, this limitation still arises during the execution of the research. In this research, 12 stations were selected to provide the precipitation data as well as the temperature, wind speeds and humidity data from meteorological stations. Among these 12 stations there are five meteorological stations selected for the study. Moreover, as seen in Figure 2, among the 12 stations, there are only three rainfall stations that are located precisely inside the upstream Bengawan Solo catchment. In fact, there are more than three rainfall stations that exist inside the catchment. However, these stations do not have complete data for the desired modelling period and the quality of these data are questionable. Furthermore, there are no meteorological stations existed inside the study area. The meteorological station is an important factor for hydrological modelling because the data such as wind speeds, temperature and humidity could only be obtained from these stations. Therefore, to overcome this problem, the stations located outside the study area are also selected mainly due to the necessity of the meteorological data.

To assess whether using the stations located outside the study area affected the streamflow generated by the model, during the modelling phase, the SWAT+ model was used to simulate the streamflow using the stations located inside and surrounding the study area. For the precipitation input, the stations used are Polokarto, Jumantono and Tawangmangu where this location are located inside. The surrounding stations used area Delingan and Kemuning which located not far on north side of the study area. For the other meteorological data (wind speeds, temperature and humidity) still obtained from the meteorological stations namely Cengklik, Kendunguling, Ketro, Ngancar and Patihan which these stations are located approximately 10-20 km away from the study area. However, the precipitation data from these meteorological stations are not included for the SWAT+ model. This model then used to simulate the uncalibrated and calibrated scenario. The results shows that all of the BIAS, MAE and NSE values of this scenarios are exactly the same as the model that running using all of the 12 stations for the precipitation input for all scenarios. According to Felix and Jung (2022), within the SWAT+ model, there is a build in interpolation method called Nearest Neighbor (NN). It was assumed using this method, the SWAT+ model selects the relevant inputs (precipitation) for the study area according to the DEM model. Moreover, due to no meteorological data that located inside or near the study area, the SWAT+ model might use the data from the meteorological stations near the study area. Therefore, it was found that including the stations outside the study area does not have an impact towards the simulated results. Furthermore, the catchment is only covered by two pixels of CMOPRH SPP and four pixels of MSWEP SPP due to the size of the catchment that is relatively small. To have a comparable state with the model that use observed precipitation, the model that use SPPs will be simulated using the pixels that located outside the study area that matching with the location of the in-situ stations that used in model that use observed precipitation.

Moreover, another limitation was found during the comparison of the SPPs, the evaluation could not be conducted 'apple to apple' due to the different spatial resolutions of these products. MSWEP has a higher resolution than CMORPH which makes the reference for testing the performance different between these products. The only implementation that could be conducted was to merge all the pixels data and compare the general results of these products. However, the different grid size makes the MSWEP SPP with higher resolutions has a lower BIAS and MAE compared to CMORPH SPP. This could be due to the location of the in-situ stations that are located not far from one another which makes there are four pixels from CMORPH products that contain more than one in-situ station in a pixel. MSWEP on the other hand, have a higher resolution than CMOPRH which makes more in-situ stations can be represented using one pixel.

Another limitation that was found during the modelling stage is the performance of the model that use CMORPH SPP not improving but rather decreasing. This could be due to the fact that these parameters were obtained using observed precipitation. However, the focus of this study is to evaluate the accuracy between the satellite precipitation products and the observed precipitation. Therefore, to have a uniform reference for the comparison, the model used for running the satellite precipitation will use same calibration parameters that were obtained from the analysis that used observed precipitation as the reference. However, in a more detailed analysis in the future, it is suggested to redo the calibration obtaining more suitable parameters using different inputs for the model.

Lastly, the bias-corrected precipitation conducted at the end of the evaluation does not show a good result except for the BIAS indicators. This could be influenced by several factors. One of the factors was due to the data from all pixels (9 MSWEP pixels) being merged into one dataset. This merged dataset could form a different distribution formula compared to the distribution factors that obtained using per pixel data. This could be reason that the quantile mapping function might generate the optimal distribution function that is more suitable for the combined data and not the aggregated data which is not really accurate. For further study, it also suggested that the quantile mapping technique is conducted pixel per pixel to generate a more accurate distribution function per area.

4.2. Comparisons with other literature

The results of the modelling will be compared with various study that conducted to assess these SPPs (CMORPH and MSWEP). One of the studies was conducted by Beck et al. (2017) where CMORPH and MSWEP SPPs are assessed in tropical area. The NSE value for the CMORPH and MSWEP obtained from this study are 0.31 and 0.53 respectively which is almost similar to the results that found in this research (0.33 for CMORPH and 0.51 for MSWEP). Another study is conducted by N. M. Reddy and Saravanan (2022) at Godavari River basin in India where the CMORPH and MSWEP also assessed for their performance. The NSE for CMORPH and MSWEP from this study are 0.36 and 0.75 respectively. Clearly, from the results of this research and from the literatures, the performance of MSWEP SPP in hydrological modelling is higher than CMORPH SPP.

4.3. Potentials for further study

Apart from the limitations and the uncertainty of the satellite products that found during the research, the satellite product could still be a relevant input for the hydrological modelling. Considering the data scarcity especially in Indonesia which also faced during the research, the satellite precipitation products especially MSWEP could be one of the alternatives to replace the data obtained from the in-situ stations. Using satellite precipitation could reduce the complexity and cost that often arise when conducting the field observation to obtain precipitation data. From this research, the MSWEP product seems accurate in estimating the precipitation in Indonesia. However, there should be a more analysis especially regarding the bias correction for this data to obtain a more accurate precipitation data from this product. With a proper bias correction method, the MSWEP product could be used for another study area in Indonesia.

5. Conclusion and Recommendations

The findings that observed during the study will be explained according to the research questions that mentioned in the introduction of this report. Moreover, at the end of this sections there are recommendations that will be described for helping further study in this field.

5.1. Conclusion

In conclusion, this research was conducted mainly to investigate the performance of the satellite precipitation products (SPPs) especially in the application for hydrological modelling. The satellite products used in this investigation are CMORPH and MSWEP which have been discussed by many researchers for their outstanding performance in estimating the actual precipitation. The SPPs can be used as an alternative to replacing the gauge observations for getting the precipitation data. During the study there are several key findings that were observed. The first finding is answering the first research question. It was found that the performance of both SPPs in estimating the actual precipitation in the study area is almost similar for merged data. However, in the aggregated data per pixel locations, the MSWEP product seems to have a lower BIAS and MAE compared to the CMORPH products.

Referring to the second research question, the comparison of the streamflow generated by the SWAT+ model using observed precipitation with the observed streamflow has shown a promising result. Moreover, it was found that the calibration process of the model has a significant impact in determining the results simulated by the model. It was found that the NSE value is significantly increasing after the calibration from 0.20 to 0.59 as well as improvement in BIAS and MAE from -0.85 m^3/s to 0.05 m^3/s and from 7.01 m^3/s to 4.27 m^3/s respectively.

The next finding is relating to the performance of the SPPs in hydrological modelling which referring to the third research question. It was proved by using the SWAT+ models, the MSWEP-generated streamflow has shown significantly higher performance of NSE, BIAS and MAE compared to the streamflow that generated using CMORPH precipitation. The streamflow generated using MSWEP has obtained the NSE value of 0.51 during the five years of calibration period when compared to the observed streamflow. When compared with the streamflow generated by the SWAT+ model using observed precipitation, the MSWEP even obtained a higher NSE value of 0.75 during the calibration period. This shows that MSWEP SPP and the observed precipitation have almost similar characteristics. Therefore, for hydrological modelling, the MSWEP precipitation product is performs better than the CMORPH products.

Lastly, regarding the last research question, the quantile mapping bias correction technique was conducted to minimize the bias of MSWEP SPP. However, in the comparison for the precipitation data before and after the bias corrections the improvement only observed in the BIAS indicators. The MAE indictor for the bias-corrected data is slightly increasing compared to before correction. Then, the performance of the SWAT+ model that running this data shows a decreasing performance in the NSE and MAE indicators event though the BIAS is showing an improvement.

5.2. Recommendations

During the study, there are several things that could have done better to achieve better results. The first recommendation is regarding the performance of SWAT+ model. In this research, it was found that the calibration processes have a significant impact that could improve the performance of the model. However, due to the objectives of the research that focusing on comparing the performance of the satellite precipitation products especially in hydrological modelling, the calibration was conducted only for the SWAT+ model that simulating the streamflow using observed precipitation. The models that use satellite products are calibrated using the parameter that obtained using the observed precipitation. It is recommended that for each model that running the satellite products need to be recalibrated to have a better performance. As well as after the bias-correction, the model that will use the bias corrected data need to be recalibrated to fit the precipitation input. Moreover, as described in section 2.2.3, SWAT+ has another feature called soft calibration which referring to the calibration process that focus more on the soft data. Therefore, for further study, it is recommended to recalibrate the model before running the different types of precipitation input.

Another recommendation is regarding the bias correction method as described in previous section, the bias correction technique used in this research does not yield a significant improvement both for the precipitation data and the model performance. Therefore, further research is needed regarding the suitable bias correction technique for the satellite precipitation products especially MSWEP to yield a more accurate result.

Bibliography

Aloui, S., Mazzoni, A., Elomri, A., Aouissi, J., Boufekane, A., & Zghibi, A. (2023). A review of Soil and Water Assessment Tool (SWAT) studies of Mediterranean catchments: Applications, feasibility, and future directions. *Journal of Environmental Management*, *326*, 116799. https://doi.org/10.1016/j.jenvman.2022.116799

Auliyani, D., & Wahyuningrum, N. (2021). Rainfall variability based on the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) in Lesti watershed, Java Island, Indonesia. *IOP Conference Series*, *874*(1), 012003. https://doi.org/10.1088/1755-1315/874/1/012003

Beck, H. E., Van Dijk, A. I. J. M., Levizzani, V., Schellekens, J., Miralles, D. G., Martens, B., & De Roo, A. (2017). MSWEP: 3-hourly 0.25° global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data. *Hydrology and Earth System Sciences*, *21*(1), 589–615. https://doi.org/10.5194/hess-21-589-2017

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I. J. M., Weedon, G. P., Brocca, L., Pappenberger, F., Huffman, G. J., & Wood, E. F. (2017). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences*, *21*(12), 6201–6217. https://doi.org/10.5194/hess-21-6201-2017

Behrangi, A., Khakbaz, B., Jaw, T. C., AghaKouchak, A., Hsu, K., & Sorooshian, S. (2011). Hydrologic evaluation of satellite precipitation products over a mid-size basin. *Journal of Hydrology*, *397*(3–4), 225–237. https://doi.org/10.1016/j.jhydrol.2010.11.043

Bergström, S. (1991). Principles and confidence in hydrological modelling. *Hydrology Research*, *22*(2), 123–136. https://doi.org/10.2166/nh.1991.0009

Blair, P. H., & Buytaert, W. (2016). Socio-hydrological modelling: a review asking "why, what and how?" *Hydrology and Earth System Sciences*, *20*(1), 443–478. https://doi.org/10.5194/hess-20-443-2016

Chawanda, C. J. (2018, September 18). *Using soft data to calibrate SWAT+ model*. SWAT Model. Retrieved September 5, 2023, from https://swat.tamu.edu/media/116097/a1-2-chawanda.pdf

Chen, H., Yong, B., Gourley, J. J., Liu, J., Ren, L., Wang, W., Hong, Y., & Zhang, J. (2019). Impact of the crucial geographic and climatic factors on the input source errors of GPM-based global satellite precipitation estimates. *Journal of Hydrology*, *575*, 1–16. https://doi.org/10.1016/j.jhydrol.2019.05.020

Cherif, R., Bouteffeha, M., Gargouri-Ellouze, E., & Eslamian, S. (2023). Hydrologic models classification, calibration, and validation. In *Elsevier eBooks* (pp. 155–168). https://doi.org/10.1016/b978-0-12-821961-4.00023-3

DEMNAS. (2023, August 17). Retrieved August 16, 2023, from https://tanahair.indonesia.go.id/demnas/#/

Enayati, M., Bozorg-Haddad, O., Bazrafshan, J., Hejabi, S., & Chu, X. (2020). Bias correction capabilities of quantile mapping methods for rainfall and temperature variables. *Journal of Water and Climate Change*, *12*(2), 401–419. https://doi.org/10.2166/wcc.2020.261

FAO/UNESCO Soil Map of the World | FAO SOILS PORTAL | Food and Agriculture Organization of the United Nations. (2023, April). Retrieved June 6, 2023, from https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/

Felix, M. L., & Jung, K. (2022). Impacts of Spatial Interpolation Methods on Daily Streamflow Predictions with SWAT. *Water*, *14*(20), 3340. https://doi.org/10.3390/w14203340

Ghimire, U., Srinivasan, G., & Agarwal, A. (2018). Assessment of rainfall bias correction techniques for improved hydrological simulation. *International Journal of Climatology*, *39*(4), 2386–2399. https://doi.org/10.1002/joc.5959

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martínez, G. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, *377*(1–2), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Jajarmizadeh, M., Harun, S., & Salarpour, M. (2012). A review on theoretical consideration and Types of models in hydrology. *Journal of Environmental Science and Technology*, *5*(5), 249–261. https://doi.org/10.3923/jest.2012.249.261

Jiang, S., Liu, S., Ren, L., Yong, B., Zhang, L., Wang, M., Lu, Y., & He, Y. (2017). Hydrologic Evaluation of Six High Resolution Satellite Precipitation Products in Capturing Extreme Precipitation and Streamflow over a Medium-Sized Basin in China. *Water*, *10*(1), 25. https://doi.org/10.3390/w10010025

Joyce, R., Janowiak, J. E., Arkin, P. A., & Xie, P. (2004). CMORPH: A Method that Produces Global Precipitation Estimates from Passive Microwave and Infrared Data at High Spatial and Temporal Resolution. *Journal of Hydrometeorology*, *5*(3), 487–503. https://doi.org/10.1175/1525-7541(2004)005

Katiraie-Boroujerdy, P., Nasrollahi, N., Hsu, K., & Sorooshian, S. (2013). Evaluation of satellite-based precipitation estimation over Iran. *Journal of Arid Environments*, *97*, 205–219. https://doi.org/10.1016/j.jaridenv.2013.05.013

Kauffeldt, A., Halldin, S., Rodhe, A., Xu, C., & Westerberg, I. (2013). Disinformative data in large-scale hydrological modelling. *Hydrology and Earth System Sciences*, *17*(7), 2845–2857. https://doi.org/10.5194/hess-17-2845-2013

Kidd, C., & Levizzani, V. (2011). Status of satellite precipitation retrievals. *Hydrology and Earth System Sciences*, *15*(4), 1109–1116. https://doi.org/10.5194/hess-15-1109-2011

Le, M., Lakshmi, V., Bolten, J. D., & Du Bui, D. (2020). Adequacy of satellite-derived precipitation estimate for hydrological modeling in Vietnam basins. *Journal of Hydrology*, *586*, 124820. https://doi.org/10.1016/j.jhydrol.2020.124820

Lee, G., Nguyen, D. H., & Le, X. (2023). A Novel Framework for Correcting Satellite-Based Precipitation Products for Watersheds with Discontinuous Observed Data, Case Study in Mekong River Basin. *Remote Sensing*, *15*(3), 630. https://doi.org/10.3390/rs15030630

Liu, Z., Shie, C., Li, A., & Meyer, D. (2020). NASA Global Satellite and Model Data products and services for tropical meteorology and climatology. *Remote Sensing*, *12*(17), 2821. https://doi.org/10.3390/rs12172821

Maggioni, V., & Massari, C. (2018). On the performance of satellite precipitation products in riverine flood modeling: A review. *Journal of Hydrology*, *558*, 214–224. https://doi.org/10.1016/j.jhydrol.2018.01.039

Michaelides, S., Levizzani, V., Anagnostou, E. N., Bauer, P., Kasparis, T., & Lane, J. E. (2009). Precipitation: Measurement, remote sensing, climatology and modeling. *Atmospheric Research*, *94*(4), 512–533. https://doi.org/10.1016/j.atmosres.2009.08.017

Mostafa, T., Brissette, F., & Arsenault, R. (2020). Evaluation of the ERA5 reanalysis as a potential reference dataset for hydrological modelling over North America. *Hydrology and Earth System Sciences*, *24*(5), 2527–2544. https://doi.org/10.5194/hess-24-2527-2020

MSWEP - GLOH2O. (2023, August 17). Retrieved May 10, 2023, from https://www.gloh2o.org/mswep/

Nash, J., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, *10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Panjwani, S., Kumar, S. N., & Ahuja, L. (2020). Bias correction of GCM data using quantile mapping technique. In *Springer eBooks* (pp. 617–621). https://doi.org/10.1007/978-981-15-5077-5_55

Pechlivanidis, I., Jackson, B., McIntyre, N., & Wheater, H. S. (2013). Catchment scale hydrological modelling: A review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. *Global Nest Journal*, *13*(3), 193–214. https://doi.org/10.30955/gnj.000778

Peng, J., Li, S., Huang, Y., Ling, Y., Li, Z., Bao, A., Chen, X., Kurban, A., & De Maeyer, P. (2021). Satellite-Based precipitation datasets evaluation using gauge observation and hydrological modeling in a typical arid land watershed of central Asia. *Remote Sensing*, *13*(2), 221. https://doi.org/10.3390/rs13020221

Polong, F., Pham, Q. B., Anh, D. T., Rahman, K. U., Shahid, M. A., & Alharbi, R. S. (2022). Evaluation and comparison of four satellite-based precipitation products over the upper Tana River Basin. *International Journal of Environmental Science and Technology*, *20*(1), 843–858. https://doi.org/10.1007/s13762-022-03942-1

Precipitation - CMORPH CDR. (2023, July 31). National Centers for Environmental Information (NCEI). Retrieved May 4, 2023, from https://www.ncei.noaa.gov/products/climate-data-records/precipitation-cmorph

Rahmawati, N., & Lubczynski, M. (2017). Validation of satellite daily rainfall estimates in complex terrain of Bali Island, Indonesia. *Theoretical and Applied Climatology*, *134*(1–2), 513–532. https://doi.org/10.1007/s00704-017-2290-7

Reddy, N. M., & Saravanan, S. (2022). Evaluation of the accuracy of seven gridded satellite precipitation products over the Godavari River basin, India. *International Journal of Environmental Science and Technology*, *20*(9), 10179–10204. https://doi.org/10.1007/s13762-022-04524-x

Reddy, P. J. R. (2005). *A Text book of Hydrology*. Firewall Media.

Ren, P., Li, J., Feng, P., Guo, Y., & Ma, Q. (2018). Evaluation of Multiple Satellite Precipitation Products and Their Use in Hydrological Modelling over the Luanhe River Basin, China. *Water*, *10*(6), 677. https://doi.org/10.3390/w10060677

Rustanto, A., Booij, M. J., Wösten, H., & Hoekstra, A. Y. (2017). Application and recalibration of soil water retention pedotransfer functions in a tropical upstream catchment: case study in Bengawan Solo, Indonesia. *Journal of Hydrology and Hydromechanics*, *65*(3), 307–320. https://doi.org/10.1515/johh-2017-0020

Rustinsyah, R., Prasetyo, R. A., & Adib, M. (2021). Social capital for flood disaster management: Case study of flooding in a village of Bengawan Solo Riverbank, Tuban, East Java Province. *International Journal of Disaster Risk Reduction*, *52*, 101963. https://doi.org/10.1016/j.ijdrr.2020.101963

Salvadore, E., Bronders, J., & Batelaan, O. (2015). Hydrological modelling of urbanized catchments: A review and future directions. *Journal of Hydrology*, *529*, 62–81. https://doi.org/10.1016/j.jhydrol.2015.06.028

Schaefli, B., & Gupta, H. V. (2007). Do Nash values have value? *Hydrological Processes*, *21*(15), 2075–2080. https://doi.org/10.1002/hyp.6825

Senent-Aparicio, J., George, C., & Srinivasan, R. (2021). Introducing a new post-processing tool for the SWAT+ model to evaluate environmental flows. *Environmental Modelling and Software*, *136*, 104944. https://doi.org/10.1016/j.envsoft.2020.104944

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M., & Xu, C. (2015). Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications. *Journal of Hydrology*, *523*, 739–757. https://doi.org/10.1016/j.jhydrol.2015.02.013

Su, J., Li, X., Ren, W., Lü, H., & Zheng, D. (2021). How reliable are the satellite-based precipitation estimations in guiding hydrological modelling in South China? *Journal of Hydrology*, *602*, 126705. https://doi.org/10.1016/j.jhydrol.2021.126705

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., & Hsu, K. (2018). A review of global precipitation data sets: data sources, estimation, and intercomparisons. *Reviews of Geophysics*, *56*(1), 79–107. https://doi.org/10.1002/2017rg000574

Sun, R., Yuan, H., Liu, X., & Jiang, X. (2016). Evaluation of the latest satellite–gauge precipitation products and their hydrologic applications over the Huaihe River basin. *Journal of Hydrology*, *536*, 302–319. https://doi.org/10.1016/j.jhydrol.2016.02.054

Suroso, S., Santoso, P. B., Birkinshaw, S., Kilsby, C., Bárdossy, A., & Aldrian, E. (2023). Assessment of TRMM rainfall data for flood modelling in three contrasting catchments in Java, Indonesia. *Journal of Hydroinformatics*, *25*(3), 797–814. https://doi.org/10.2166/hydro.2023.132

Tan, M. L., Gassman, P. W., & Cracknell, A. P. (2017). Assessment of three Long-Term Gridded Climate products for Hydro-Climatic simulations in tropical River basins. *Water*, *9*(3), 229. https://doi.org/10.3390/w9030229

Wang, N., Liu, W., Sun, F., Yao, Z., Wang, H., & Liu, W. (2020). Evaluating satellite-based and reanalysis precipitation datasets with gauge-observed data and hydrological modeling in the Xihe River Basin, China. *Atmospheric Research*, *234*, 104746. https://doi.org/10.1016/j.atmosres.2019.104746

Wang, Z., Zhong, R., & Chen, J. (2017). Evaluation of the GPM IMERG satellite-based precipitation products and the hydrological utility. *Atmospheric Research*, *196*, 151–163. https://doi.org/10.1016/j.atmosres.2017.06.020

Wati, T., Hadi, T. W., & Sopaheluwakan, A. (2022). Statistics of the performance of gridded precipitation datasets in Indonesia. *Advances in Meteorology*, *2022*, 1–11. https://doi.org/10.1155/2022/7995761

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*, 79–82. https://doi.org/10.3354/cr030079

Yuan, F., Zhang, L., Win, K. W. W., Ren, L., Zhao, C., Zhu, Y., Jiang, S., & Liu, Y. (2017). Assessment of GPM and TRMM Multi-Satellite precipitation products in streamflow simulations in a Data-Sparse mountainous watershed in Myanmar. *Remote Sensing*, *9*(3), 302. https://doi.org/10.3390/rs9030302

Zhao, C., Ren, L., Yuan, F., Zhang, L., Jiang, S., Shi, J., Chen, T., Liu, S., Yang, X., Liu, Y., & Fernandez-Rodriguez, E. (2020). Statistical and hydrological evaluations of multiple satellite precipitation products in the Yellow River Source region of China. *Water*, *12*(11), 3082. https://doi.org/10.3390/w12113082

Appendix A – Overview of satellite precipitation products (SPPs)

Table A. 1. Overview of currently available SPPs

Satellite Product	Descriptions	Spatial Resolution	Temporal Resolution	Temporal Availability	Assessment Method	Temporal Period (for hydrological modelling)	Region of Application (Perform Best at)	Reference
CHIRPS v2.0	Climate Hazards Group InfraRed Precipitation with Station Data	0.05°	Daily	1981 - Present	Hydrological Modelling	2000 - 2017	Vietnam	(Le et al., 2020)
TMPA 3B42RT	TRMM Multi-Satellite Precipitation Analysis (continuity of TRMM)	0.25°	3-Hourly	2000 - Present	Hydrological Modelling (SWAT Model)	2001 - 2012	China	(Ren et al., 2018)
TMPA 3B42V7	TRMM Multi-Satellite Precipitation Analysis v.7(continuity of TRMM)	0.25°	3-Hourly	2001 - Present	Hydrological Modelling	2000 - 2013	China	(Jiang et al., 2017)
PERSIANN-CDR	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record	0.25°	6-Hourly	1983 - Present	Hydrological Modelling	1983 - 1992	Malaysia	(Tan et al., 2017)
ARC-2	Academic Research Consortium	0.1°	Daily	1984 - Present	Comparison to rain-gauge data	-	Africa	(Polong et al., 2022)
CMORPH	CPC MORPHing Technique	0.25°	30-Minutes	2002 - Present	Hydrological Modelling	2003-2008	Arkansas, United States	(Behrangi et al., 2011)
MSWEP v1.2	Multi-Source Weighted-Ensemble Precipitation	0.25°	3-Hourly	1979 - 2015	Hydrological Modelling	2001 - 2012	Globally (Temperate, Cold and Tropical Regions)	(Beck et al., 2017)
MSWEP v2.0	Multi-Source Weighted-Ensemble Precipitation	0.1°	3-Hourly	1979 - Present	Hydrological Modelling	2001 - 2012	Globally (Temperate, Cold and Tropical Regions)	(Beck et al., 2017)
IMERG-F	Integrated Multi-satellitE Retrievals for GPM - Final run	0.1°	30-Minutes	2014 - Present	Hydrological Modelling	2014 - 2015	South China	(Wang et al., 2017)
GSMaP	Global Satellite Mapping of Precipitation	0.1°	Hourly	2000 - Present	Comparison to rain-gauge data	2014 - 2016	China	(Zhao et al., 2020)