The Comparison of Reservoir Impoundment Duration between Ground Observation and Satellite Precipitation Product over Karian, Indonesia

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Abstract.

The initial filling phase of reservoirs is a critical period that demands close supervision to ensure safety and functionality. During this phase, the dam is slowly filled with water, submerging floodplains until it reaches its intended storage capacity. This process assesses the response of the dam to water filling and its overall safety, with continuous monitoring and evaluation against design standards. The duration and rate of filling depend on several factors, i.e., precipitation, dam height, and hydropower plant sensitivity; thus, precipitation was the prominent driving force. However, as continuous precipitation data, multi-satellite global precipitation maps under the Global Precipitation Measurement near-real-time (GSMaP NRT) satellite products offer an alternative but tend to underestimate or overestimate rainfall values, posing challenges for accurate predictions. Bias correction methods of GSMaP NRT product in the spanning period of 2005–2022 demonstrated in agreement with ground observation data through the application of the artificial neural network (ANN) method to reduce the error bias to produce reliable results. This study highlights the importance of the impoundment period for reservoir sedimentation and overall dam safety. It emphasises the need for accurate precipitation data in reservoir management and recommends rigorous bias correction when using satellite data to substitute ground measurements.

Keywords: *Reservoir, Impoundment, GSMaP and Precipitation.*

I. INTRODUCTION

Reservoir first filling is a critical phase, requiring intensive supervision. During this initial phase of reservoir impoundment, the dam is gradually filled with water, inundating the floodplains until it reaches the intended storage capacity to assess the response of the dam to water filling and ensure its safety and functionality. Throughout this period, the dam's behaviour to water level rise is consistently monitored and assessed against the design (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2019).This period tests the seepage resistance of the dam, foundation, abutments, and reservoir rim for the first time. In addition, the reservoir load tests the structural stability of the dam. Instrumentation data during this phase provide early indications of unusual or unexpected performance and establish baseline measurements for future operating conditions (Task Committee to Revise Guidelines for Dam Instrumentation and de Rubertis, 2018).During the impoundment period, the water level in the reservoir is gradually raised in multiple stages. At each stage, the filling is paused to allow adequate time for monitoring, data collection, and evaluation of the dam's performance and its foundation. Monitoring indices change with the water load and other factors, so impoundment is crucial to dam safety. The safety assessment is based on the comparison of the monitoring data with reference values. Consequently, the impoundment phase holds immense significance for ensuring the safety of the dam. Given the occurrence of numerous engineering accidents during this particular period, becomes imperative to thoroughly analyse the operational behaviour of the dam to guarantee its safe operation (ICOLD, 2018; Leitão et al., 2023; Wu et al., 2016).The failure of an earth or rockfill dam could happen by overtopping, slope failure, sliding, and internal erosion (Terzaghi et al., 1996). However, during the initial impoundment, the most possible failure to occur is slope failure or internal corrosion (Kurter, 2022).From a safety point of view, the first filling can be considered the most important stage throughout the life of a dam, in particular the rockfill type. This type of dam typically involves sudden settlement during the first filling of the reservoir resulting in a collapse settlement (Mahinroosta et al., 2015).The filling rate and duration largely depend on the amount of precipitation, dam height in hydropower dams, the sensitivity of power plants, and their regular tests. Generally, an impounding period of a reservoir requires at least 1-2 years. Table 1 shows different first-filling durations for several reservoirs.

Table 1. Impoundment Duration of Reservoirs

Reservoir	Impoundment Start Date	Impoundment End Date	Duration	Reference
Kozjak, Macedonia	2003	2004	365 days	(Ljupcho and Stevcho, 2017)
Alto Ceira II, Portugal	June 28th, 2013	February 11th, 2014	228 days	(Leitão et al., 2023)
Jatigede, Indonesia	August 31st, 2015	April 7th, 2017	585 days	(Biro Komunikasi Publik Kementerian PUPR, 2015; Pitoko, 2017)

However, the lack of rainfall data, such as inaccuracies in radar rainfall data In the Gotavnand Dam, this inconsistent pattern prevails due to fluctuations in precipitation, dam height, and the demands of the power plant, resulting in the reservoir not reaching its expected water level with a continuous trend (Mahinroosta et al., 2015; Wiltshire, 2002).Uneven distribution of ground gauge measurement networks, results in uncertainty and low accuracy in predicting the reservoir impoundment rate owning to insufficient rainfall input accuracy, model calibrations, and data assimilation processes (Kure et al., 2013).Still, one of the most feasible alternatives is Satellite Precipitation Product (SPP) such as the Tropical Rainfall Measuring Mission (TRMM) and the Global Satellite Mapping of Precipitation (GSMaP). An important characteristic of SPPs that must be considered is that these estimates tend to underestimate or overestimate the rain values (Fu et al., 2011; Jiang et al., 2019; Rozante et al., 2018).However, these tendencies of overestimation or underestimation can vary from region to region. Especially when observed in smaller regions with specific characteristics of relief and land cover, as their effects influence the radiation, thermodynamics and physics of clouds in each region. Furthermore, the meteorological characteristics of each region are different. These aspects consequently influence the response of the satellite sensors to capture the precipitation that occurred in the region (Palharini et al., 2021). Several previous studies suggest that the underestimation that occurred in the GSMaP products was due to orographic effects.

Over coastal mountain ranges, heavy rainfall can be caused by shallow orographic rainfall, which is inconsistent with the assumption in the PMW algorithm that heavy rainfall results from deep clouds with significant ice (Kubota et al., 2020, 2009).A study has shown that despite the inaccuracies, the use of GSMaP rainfall data in Jakarta is applicable due to the negligible orographic effect since only the rainfall event in 2018 in the high altitude zones was difficult to capture (Priyambodoho et al., 2021).Artificial intelligence (AI) can be implemented to correct the inaccuracies. Multi-Layer Perceptron (MLP) is a type of feed-forward neural network consisting of an input layer, one or more hidden layers, and an output layer. MLPs are designed to model complex non-linear relationships between input and output data using a series of interconnected neurons. Each neuron in one layer is connected to every neuron in the next layer, forming a fully connected network. MLPs use activation functions such as sigmoid, tanh, or ReLU to introduce non-linearity, enabling the network to learn from data through a process called backpropagation, which adjusts the connection weights to minimize prediction errors (Bikku 2020). Neural networks are also applied to correct biases in satellite-based precipitation estimates by comparing them with ground observations. For example, a neural network can be trained to predict accurate precipitation values using satellite data as input, making satellite estimates closer to observational data (Le et al. 2020).The impoundment period of a reservoir became important in reservoir sedimentation studies.

It is important to identify and locate all existing reservoirs in a basin where a sediment study is to be made as the existence of a dam structure may alter both the sediment yield and the water discharge duration curve. Therefore, the date of impoundment is important so that observed inflowing sediment loads may be coordinated with whatever conditions existed in the basin during the periods selected for calibration and verification (Williams, 1997).The impoundment period is also important to ensure that the water level is not rapidly increasing which may lead to a collapse settlement in a dam structure. While the change in reservoir's shorelines is usually a gradual process, it is known that on at least one occasion it has been disastrous. In October 1963, a large landslide fell into the recently impounded reservoir behind the Vaiont Dam in Italy, spilling an equal volume of water over the dam into the valley below leading to a tragic loss of over 2000 lives. This catastrophe was likely due in part to seismic activity, probably triggered by the reservoir impoundment (Baxter, 1977; Rothe, 1973).Research on the construction and first filling of the Gotland embankment dam has been conducted to compare the impounding rate impact on the first filling deformation and the collapse settlement risk of the dam. The study showed that a rapid increase in water level results in greater settlement compared to the gradual increase scheme. Therefore, for a safer situation, the first impoundment of rockfill dams should be performed gradually (Mahinroosta et al., 2015). This study aims to understand the feasibility of using the GSMaP Rainfall data to estimate reservoir impoundment duration within the Karian Reservoir, Banten, Indonesia.

II. MATERIALS AND METHODS

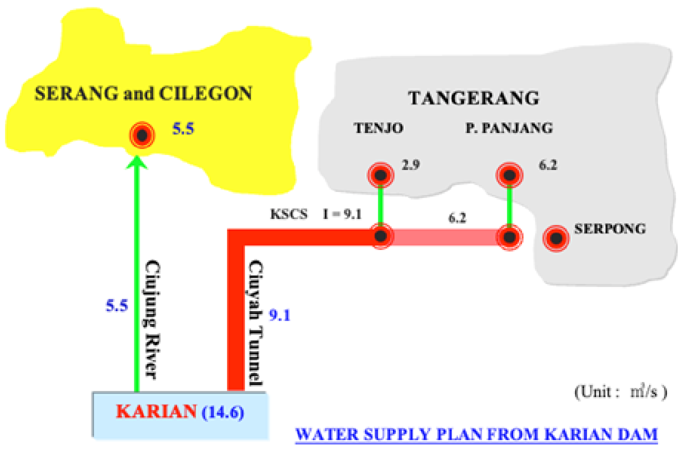
2.1 Study Area

The Karian Dam is a centre-core rockfill dam currently under construction in the downstream part of the Ciberang River with a catchment area of 288 km^2. It is located between Lebak and Bogor Regency as shown in Figure 1.

Fig 1. Location of Karian Multipurpose Dam (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2005)

The construction of the Karian Dam began in 2015 and was expected to begin its operation in 2019 (Hidayat, 2016). However, it was delayed and therefore the final date was postponed several times to 2021 (Yusron et al., 2022), 2022 (Komite Percepatan Penyediaan Infrastruktur Prioritas (KPPIP), 2022), and finally 2023 (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2023).According to the current timeline, the reservoir impoundment stage will begin in September 2023 (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2023) and to be completed within 12 months (Hidayat, 2016). It is one of the national strategic projects designed to ensure water security by supplying 9.1 m^3/s of water for the Lebak and Tangerang Regency, Tangerang and South Tangerang City, and the DKI Province through the Karian-Serpong Conveyance System, 5.5 m^3/s for Ciujung Irrigational Area, Cilegon City, and Serang Regency, and flood control for the downstream area where strategic infrastructure such as the Jakarta-Merak Toll Road and the Integrated Industrial Area is located (Figure 2).

Fig 2. Water Supply Plan of Karian Multipurpose Dam (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2005). Aside from its main purposes as water supply and flood control system, the dam also serves its function as a Mini Hydro Powerplant with the potential of generating 1.8 MW of power.

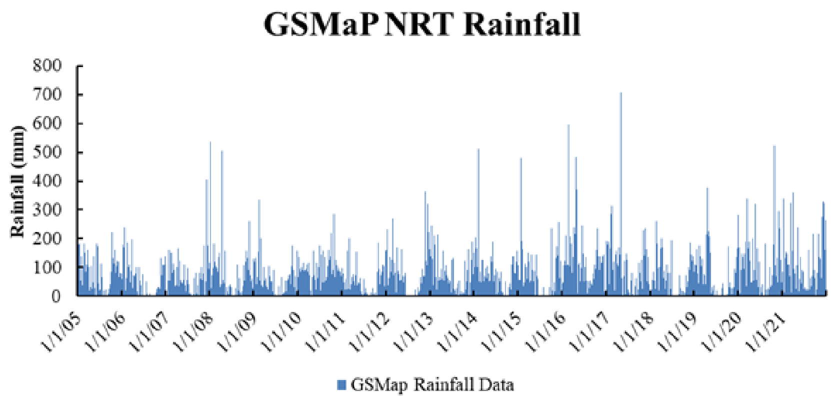


2.2 Methods

2.2.1 Satellite Rainfall Products

The GSMaP project was implemented in 2002 to develop retrieval algorithms for rainfall rates and to produce high-resolution global precipitation maps based on satellite data (Aonashi and Liu, 2000; Ushio et al., 2009). GSMaP products are distributed by the Japan Aerospace Exploration Agency (JAXA) Global Rainfall Watch. GSMaP Now, GSMaP NRT, and GSMaP MVK are provided by JAXA.Among them, GSMaP NRT is one of the standard GPM-based SPPs, which can be widely applied for monitoring various natural disasters. To further improve the retrieval accuracy, the GSMaP team of Japan Aerospace Exploration Agency (JAXA) also developed another near-real-time product, namely, the gauge-calibrated GSMaP-NRT (i.e., GSMaP-Gauge-NRT) by integrating the Climate Precipitation Center unified gauge-based precipitation data (Xie et al., 2007).In this study, we evaluated the data using GSMaP NRT between 2005-2022 as shown in Figure 3.

Fig 3. GSMaP Near Real Time (NRT) for Annual Rainfall between 2009 and 2025



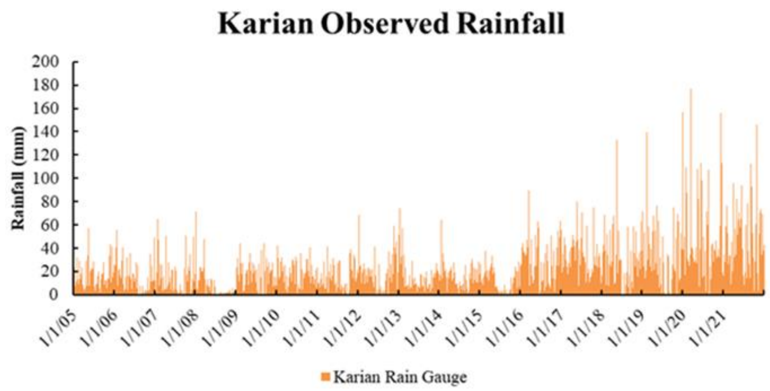
2.2.2 GSMaP Verification with Machine Learning

This study utilizes machine learning techniques to verify the precision of GSMaP satellite rainfall data. An 8-layer artificial neural network (ANN) is used, comprising one input layer, six hidden layers, and one output layer. The activation function ReLU and the 'adam' optimizer are utilized, with Mean Absolute Error (MAE) chosen as the performance metric, aligning with the optimal probabilistic metrics recommended by Liu et al. (2014). The model development process encompasses two key stages: training, involving the adjustment of neural network parameters through backpropagation, and testing, used for evaluating the model's predictive capabilities on unseen data, thus validating its real-world applicability. With an extended training duration of 2500 epochs, the study offers profound insights into the correlation between satellite and ground-based rainfall data, enhancing our comprehension of climate and meteorological patterns. These insights hold immense value across a spectrum of applications reliant on precise rainfall data, ranging from climate research to scientific and practical domains.

2.2.3 Rainfall Gauge

The catchment area of Karian Dam is covered by several observations e.g. Pasir Ona, Ciminyak Cilaki, Cimarga, and Banjar Irigasi. Observed rainfall between 2001-2021 from these stations are analysed using the Thiessen method to obtain the basin-averaged rainfall on the Karian Dam as presented in Figure 4.

Fig 4. Karian Observed Rainfall for Annual Rainfall between 2009 and 2025



2.2.4 Evaluation Index

Statistical validation methods, such as the root mean square error (RMSE) and correlation coefficients (CCs) are commonly used as evaluation indexes; these were employed to evaluate the relationship between the GSMaP and observation data (Ciabatta et al., 2015; Sharifi et al., 2019; Ur Rahman et al., 2019). The RMSE was used to compare the magnitude of the error between the GSMaP and observation data sets. CC represented the correlation between the data sets; its value ranged between zero and one. The volume bias (%) is the difference in the percentages of the total rainfall volume between the GSMaP and ground rainfall observation. It is calculated using the following equation: (100 × ((GSMaP − Observation) / Observation)) (Admojo et al., 2018; Pakoksung and Takagi, 2016; Priyambodoho et al., 2021).

2.2.5 Reservoir Impoundment Duration

The reservoir impoundment duration is estimated by accumulating the inflow volume from daily river discharge and only considering losses from evaporation throughout the process. An impoundment period is considered finished when a reservoir water level has reached the normal water level at +67.50.

By their nature, the first filling of these reservoirs occurs during floods so compared to other reservoirs there may be an increased risk that an incident requiring emergency drawdown would be detected during a period of high inflows (Andy Courtnadge et al., 2017).Several observation data are required to predict the time needed for the reservoir to be filled e.g. river discharge, evaporation, and Elevation-Area-Capacity Curve.Sabagi station is the closest automatic water level recorded (AWLR) located in the Ciberang River, 5.3 km downstream of Karian Dam (Figure 7). The observed daily mean discharge from 2014-2022 in Sabagi station is applied to estimate the inflow volume of the reservoir during the first filling period.

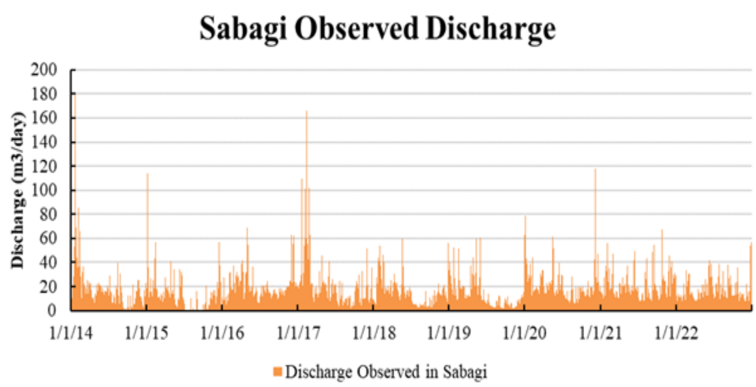
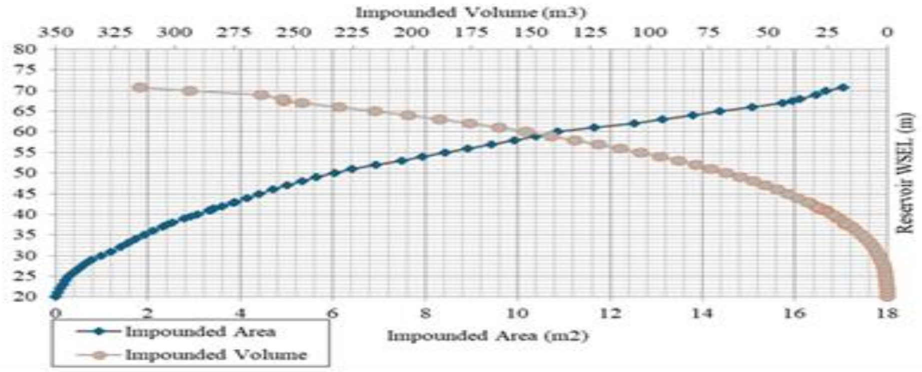


Fig 5. Observed daily discharge (m^3/day) in Sabagi Station from 2018 until 2026

In accordance with the report from the Ministry of Public Works and Public Housing which stated that the impoundment period of Karian Reservoir will begin in September, therefore this study will follow the same scheme as stated.The project area belongs to the typical humid tropical zone and weather patterns are characterized by monsoons. The west monsoon dominates the area with abundant rainfall from December through March, and the east monsoon appears with less rainfall from June through September. The monthly mean air temperature varies little throughout the year, ranging from 26 °C to 27 °C at Serang in the northern coastal plain. The relative humidity is generally high, ranging from 80% to 85% throughout almost the entire year, with some decline to about 80%. The monthly mean wind velocity at Serang ranges between 3.5 knots and 4.5 knots, and the maximum wind velocity was surveyed at 28 knots on 13-Dec-1999 at Serang station. The monthly mean sunshine duration at Serang ranges from five to six hours daily in the dry season and between three and four hours daily in the wet season. The mean evaporation of 5.0 mm per day in the project area has been calculated using the Penman Method (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2005).According to the topography, the elevation-area-capacity curve of Karian Reservoir is displayed in Figure 6. The inundated area from inflow volume is estimated from this curve to determine the amount of evaporated volume.

Fig. 6 Reservoir Elevation-Area-Capacity Curve (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2005)



The Karian catchment area has a gross area of 288 km^2, lying in between Lebak and Bogor Regency as shown in Figure 7. From an elevation of 25 m at the Karian Dam site, it rises to peaks of 1,900 m at Bintonggading Mountain. The present land use in the Karian watershed is grouped mainly into six categories, wet field comprising 17%, dry field 1%, palm plantation 10%, forest 20%, bush 50%, and housing area 2%. This project is part of the nation's strategic initiatives aimed at guaranteeing water security. Its primary goal is to provide a consistent water supply of 9.1 m^3/s to benefit the Lebak and Tangerang Regencies, Tangerang and South Tangerang Cities, as well as the DKI Jakarta Province, through the Karian-Serpong Conveyance System. Additionally, it allocates 5.5 m^3/s of water for the Ciujung Irrigational Area, Cilegon City, and Serang Regency while simultaneously serving as a flood control mechanism for the downstream region, which includes critical infrastructure such as the Jakarta-Merak Toll Road and the Integrated Industrial Area.

Further details regarding the Karian dam and reservoir operational data are displayed in Table 2 and Figure 8.

Fig 7. Karian Dam catchment area and observation site

Table 2. Karian Dam Operational Data

Technical Data	
Catchment Area	288 km^2
Inundation Area	1,740 Ha
Designed Flood Discharge (1/2 PMF)	1,850 m^3/s
Peak Discharge (PMF)	3,671 m^3/s
Reservoir Area	15.93 km^2
Total Storage	314,71 mil m^3
Active Storage	207.48 mil m^3
Flood Storage	60.80 mil m^3
Dead Storage	46.40 mil m^3
Water Supply	14.6 m^3/s
Dead Water Level	+37.50 MSL
Low Water Level	+46.00 MSL
Normal Water Level	+67.50 MSL
High Water Level	+70.85 MSL
Maximum Water Level	+71.22 MSL
Dam Crest Level	+72.50 MSL

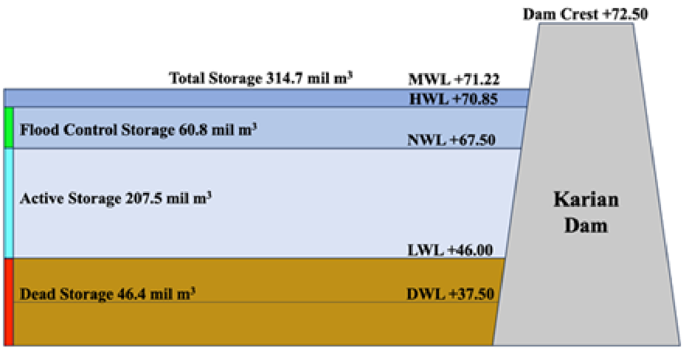


Fig 8. Karian Dam storage scheme

III. RESULTS AND DISCUSSION

This study identifies the suitability of using GSMaP NRT data as an alternative to tackle the lack of ground measurement data in estimating reservoir impoundment data using various statistical validation methods. The GSMaP observed rainfall data is compared with rainfall and flow discharge data from two observation stations near the dam as shown in Table 3.

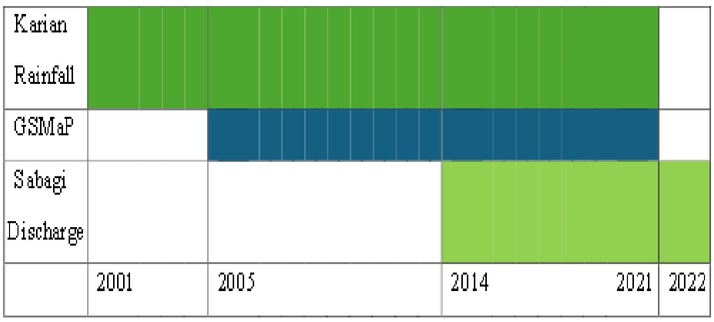


Table 3. Data availability

3.1. Rainfall and Discharge Comparison

Statistical validation methods, such as the root mean square error (RMSE) and correlation coefficients (CCs) are commonly used as evaluation indexes; these were employed to evaluate the relationship between the GSMaP and observation data (Ciabatta et al., 2015; Sharifi et al., 2019; Ur Rahman et al., 2019). The RMSE was used to compare the magnitude of the error between the GSMaP and observation data sets. CC represented the correlation between the data sets; its value ranged between zero and one. The volume bias (%) is the difference in the percentages of the total rainfall volume between the GSMaP and ground rainfall observation. It is calculated using the following equation: (100 × ((GSMaP − Observation) /Observation)) (Admojo et al., 2018; Pakoksung and Takagi, 2016; Priyambodoho et al., 2021).

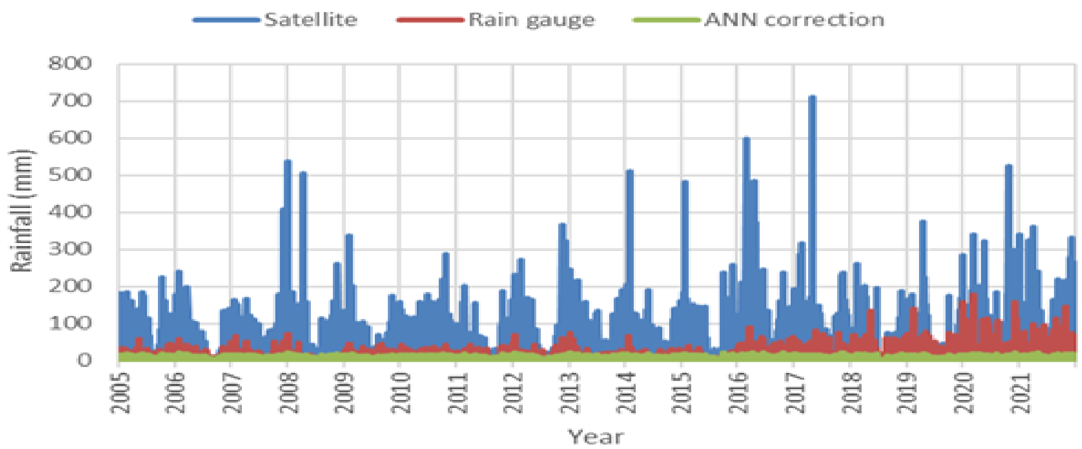


Fig 9. Comparison of daily rainfall (mm/day) from GSMap NRT (blue), observation site (red), and ANN-corrected satellite data (green)

Fig. 9. shows the comparison between observed rainfall data at the Karian Dam location between 2005-2021 and GSMaP NRT data. It can be seen that the GSMaP data have a strong tendency to overestimate the rainfall values within the area. Moreover, the figure displays daily rainfall data from the satellite (blue), which shows high variability and many extreme values, whereas the observational rainfall data from Karian (red) is more consistent. In contrast, the rainfall data that has been corrected using an Artificial Neural Network (green in Fig. 9.) demonstrates a significant reduction in variability and the extremity of rainfall values, making it more stable and aligned with the actual observational data. The correction using ANN successfully reduces bias and aligns the satellite data with observational data, resulting in more accurate and reliable data. The extreme rainfall peaks in the initial satellite data are significantly reduced after correction, showing improved alignment with the observational data.The same circumstance also appears when comparing satellite converted discharge and daily discharge data from Sabagi AWLR between 2014-2022 as displayed in.

The satellite-based discharged product was obtained through mathematical calculation by multiplying the annual rainfall with the catchment area and accounting runoff coefficient of 0.20 for forest and agricultural lands (Goel, 2011) as presented in Equation 1.

$Q = C \times R_{24} \times A$ (1)

Where:

Q = Daily discharge (m^3/day)

C = Runoff Coefficient (0.20)

R_{24} = Amount of rainfall in 24 hours (m)

A = Catchment area (m^2)

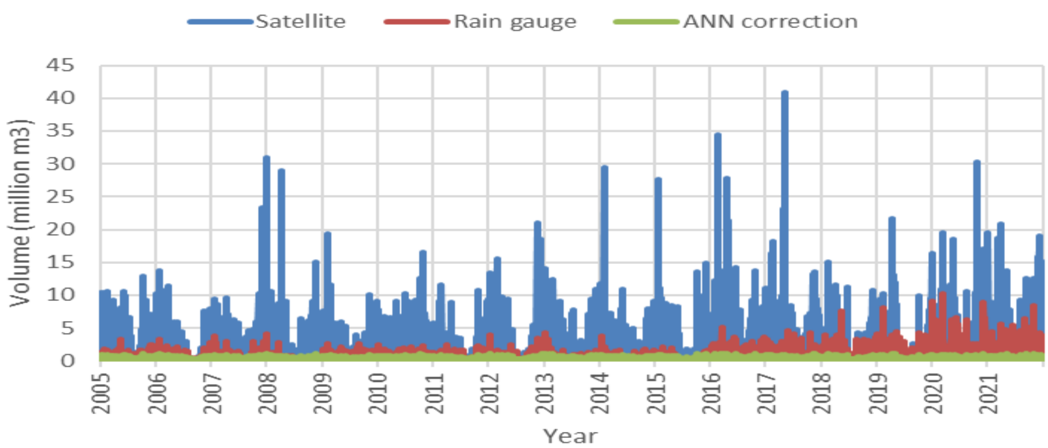


Fig 10. Comparison of daily discharge (m3/s) from GSMap NRT (blue), observation site (red), and ANN-corrected satellite data (green)

It is evident from Figure 9 and Figure 10 that the satellite product has a strong tendency to overestimate the actual rainfall value (red), proving that it is not a good fit for a replacement. The satellite data (blue) shows high variability and numerous extreme peaks, indicating notable discrepancies when contrasted with the more stable and consistent observed data. Post-correction, the satellite data demonstrates a significant reduction in variability and extreme values (green), achieving closer alignment with the observed discharge data. This adjustment underscores the ANN's effectiveness in reducing biases and enhancing the accuracy of satellite-derived discharge estimates. However, the ANN's results are generally lower than the actual rainfall.Additionally, the low CCs and large root mean square error (RMSE) as displayed in Table 4 also further confirmed the GSMaP NRT incompatibility with the gauge observation data. This verifies that the satellite product is not suitable to substitute the ground measurement data due to the lack of correlation and a large margin of error. Throughout the observation period, nearly all satellite products have either very weak (0.00-0.19) or weak correlation with observation data. The moderate correlation occurring in 2007, 2008, and 2018 are the best they can get.

Table 4. Correlation coefficient

Period	Karian Rainfall		Sabagi Discharge	
	Correlation Coefficient (CCs)	RMSE (%)	Correlation Coefficient (CCs)	RMSE (%)
2005	0.241	20.162		
2006	0.332	19.428		
2007	0.335	18.670		
2008	0.423	18.442		
2009	0.208	18.998		
2010	0.264	19.815		
2011	0.398	19.748		
2012	0.440	19.074		
2013	0.230	19.876		
2014	0.233	19.877	0.572	16.445
2015	0.237	19.190	0.264	11.159
2016	0.055	18.561	0.427	9.705
2017	0.101	19.291	0.193	22.042
2018	0.476	18.984	0.346	8.920
2019	0.415	18.911	0.415	9.136
2020	0.155	21.645	0.127	12.593
2021	0.238	19.449	0.143	12.593
2022			0.254	10.136

This phenomenon is also seen present in previous studies that found that GSMaP products tend to overestimate precipitation events of 1–20 mm/d over mainland China (Zhou et al., 2020), in Iran (Darand and Siavashi, 2021), and in the Philippines (Bagtasa, 2022). In recent years, different bias-correction methods have been developed. For example, the regression analysis and geographical differential analysis (GDA) methods have been developed to calibrate the TRMM rainfall based on gauge rainfall data and found that the rainfall calibrated by the GDA method has a high accuracy (Cheema and Bastiaanssen, 2012). A bias-correction method based on the mixed geographically weighted regression (MGWR) method for merging satellite and gauge rainfall, in which the weights were determined by four different weighting functions has also been proposed. The MGWR method improves the spatial resolution and quality of satellite rainfall and is valuable for hydrological modelling (Chao et al., 2018). An attempt to correct the bias of GSMaP NRT products has also been conducted by accounting for physical factors, including topography, season, windspeed and cloud types in Peninsular Malaysia. The model consisted of a classifier to categorize rainfall of different intensity and regression models to predict rainfall amount of different intensity classes. An ensemble tree-based learning algorithm, called random forest, was used for classification and regression. The results revealed a big improvement in near-real-time GSMaP_NRT product after bias correction, in which the bias-corrected rainfall was able to replicate the spatial distribution of observed rainfall (Ziarh et al., 2021).Therefore, GSMaP NRT data can potentially be used to replace rain gauge data if inconsistencies and errors are resolved. However, without bias correction, significant underestimation or overestimation of heavy rainfall events will be observed.

3.2. Reservoir Impoundment Duration

By their nature, the first filling of these reservoirs occurs during floods so compared to other reservoirs there may be an increased risk that an incident requiring emergency drawdown would be detected during a period of high inflows (Courtnadge et al., 2017).Inflow data used in this analysis is obtained by averaging the daily mean discharge throughout the period of data availability (2005-2021) to forecast the annual reservoir inflow during the impoundment period, which is shown in Figure 11.

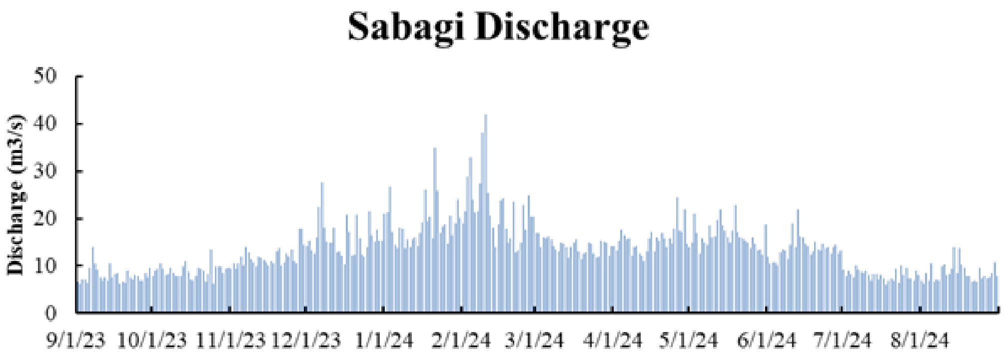


Fig 11. Predicted daily inflow into Karian reservoir from 09/02/2017 to 08/02/2028 indicated that the annual reservoir inflow during the impoundment period

Karian Reservoir is targeted to reach the normal water level of +67.50 or store at least 258.8 mil m^3 of water during the impoundment period. The local reservoir management team has stated that no flow is being discharged to the dam downstream during the impoundment period and the only water losses accounted for are from evaporation, the impoundment duration is estimated to take 149 days and 207 days from satellite and observation product respectively.Both estimations resulted in a shorter period of impoundment compared to the usual first filling duration, which generally took between 1-2 years.However, the result displays consistency with the observation and satellite measurement evaluation index where the GSMaP product tends to overestimate the product itself. Figure 12 shows that the reservoir impoundment period is shorter when predicted using satellite products in comparison to ground observation. This is because GSMap's overestimates the precipitation. Conversely, the ANN underestimates the rainfall thus it leads to a significantly longer impoundment duration. The results highlight the usefulness of the satelitte rainfall estimation and the artificial neural network, but they still require further improvement to approach the factual data.

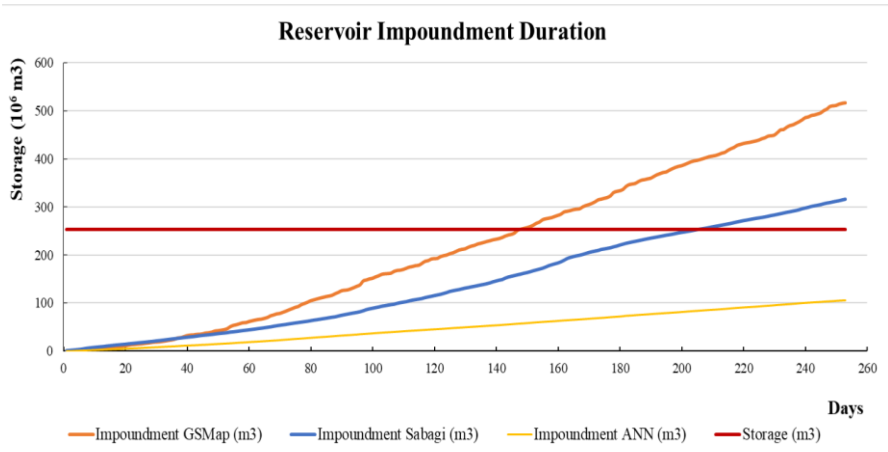


Fig 12. Karian Reservoir volume rise during impoundment period

IV. CONCLUSION

The analysis of GSMaP data and satellite-derived discharge data compared to ground observations reveals a consistent trend of overestimating rainfall values within the area. This overestimation is evident through low correlation coefficients, large root mean square error (RMSE), and weak correlations with observation data over the observation period. These findings indicate that the satellite products, including GSMaP NRT, are not suitable replacements for ground measurement data due to their lack of correlation and significant margin of error.However, it's worth noting that various bias-correction methods, such as regression analysis and geographical differential analysis, have shown promise in improving the accuracy of satellite-derived rainfall data when calibrated against gauge rainfall data. Machine learning is also employed to improve the results of the rainfall estimation. In this case, the artificial neural network provenly reduces the extreme value and the data variability.

Therefore, while GSMaP NRT data could potentially be used to replace rain gauge data if inconsistencies and errors are effectively addressed through bias correction, using uncorrected satellite data may lead to significant underestimation or overestimation of rainfall events. Furthermore, the estimation of the impoundment period for Karian Reservoir using satellite data consistently results in shorter durations compared to observation data. This finding aligns with the tendency of the GSMaP product to overestimate rainfall values, as shorter impoundment periods are predicted when using satellite data compared to ground observation. On the other hand, the implementation of the ANN improves the estimation although it has not fully solved the accuracy problem. It still undershoots the factual rainfall data which leads to the longer impoundment duration.In conclusion, this study underscores the importance of accurate rainfall data for reservoir management and suggests that while satellite data and machine learning can be valuable, rigorous bias correction is necessary to ensure its reliability in replacing ground measurement data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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