Development of a Forecasting Model for Discharges in the Manganti Irrigation System

Introduction

A robust irrigation system is the backbone of successful agriculture, ensuring that crops receive the water they need to thrive. The efficiency of such systems is pivotal in achieving optimal agricultural yields, which are essential for food security and the economic well-being of farming communities. However, the ever-changing climate poses significant challenges to maintaining consistent water availability. Events like El Niño can drastically alter weather patterns, leading to periods of drought or excessive rainfall, which in turn impact the discharge rates of rivers and reservoirs that supply irrigation systems.

To combat these uncertainties, it is crucial to develop predictive models that can forecast water discharge data. These models allow farmers and water resource managers to anticipate changes in water availability and adjust their strategies accordingly. By predicting potential reductions in water discharge, they can implement measures to conserve water during times of scarcity or optimize its use when there is an abundance.

In light of these challenges, this study introduces a novel model designed to estimate the availability of water discharge over a six-month horizon. The model integrates various data sources, including historical discharge records and weather forecasts, to provide a comprehensive outlook on future water availability. By leveraging advanced hydrological and hydraulic modeling tools and incorporating Python programming for enhanced data analysis and simulation, the model offers a sophisticated approach to irrigation management.

The model’s predictive capabilities are not only beneficial for planning irrigation schedules but also for informing broader climate change adaptation strategies. As extreme weather events become more frequent, having a reliable forecast of water discharge can guide infrastructure development, agricultural planning, and emergency preparedness efforts. This proactive approach is vital for sustaining agricultural productivity in the face of climate variability and ensuring the resilience of water-dependent communities.

Study Site

The Manganti Dam, a pivotal structure in the Ciamis regency, plays a crucial role in the agricultural prosperity of the region. It serves as the primary water source for three expansive irrigation areas (DIs), which are integral to the local farming communities. The largest of these, DI Sidareja – Cihaur, spans an impressive 9,614 hectares, providing vital sustenance to a vast expanse of farmland. Following closely is DI Cihaur, covering 4,478 hectares, which, like its counterparts, relies on the consistent flow from the dam to maintain its agricultural output. The

smallest, yet equally significant, is DI Lakbok Selatan, encompassing 1,077 hectares of irrigated land.
These irrigation areas are the lifeblood of the region's agriculture, supporting a diverse range of crops and sustaining the livelihoods of thousands of farmers. The Manganti Dam not only ensures water delivery during critical growing seasons but also enhances the region's resilience against droughts and water scarcity. The dam's management system is designed to optimize water distribution, taking into account the varying needs of each DI, thereby ensuring that water resources are utilized efficiently and sustainably.

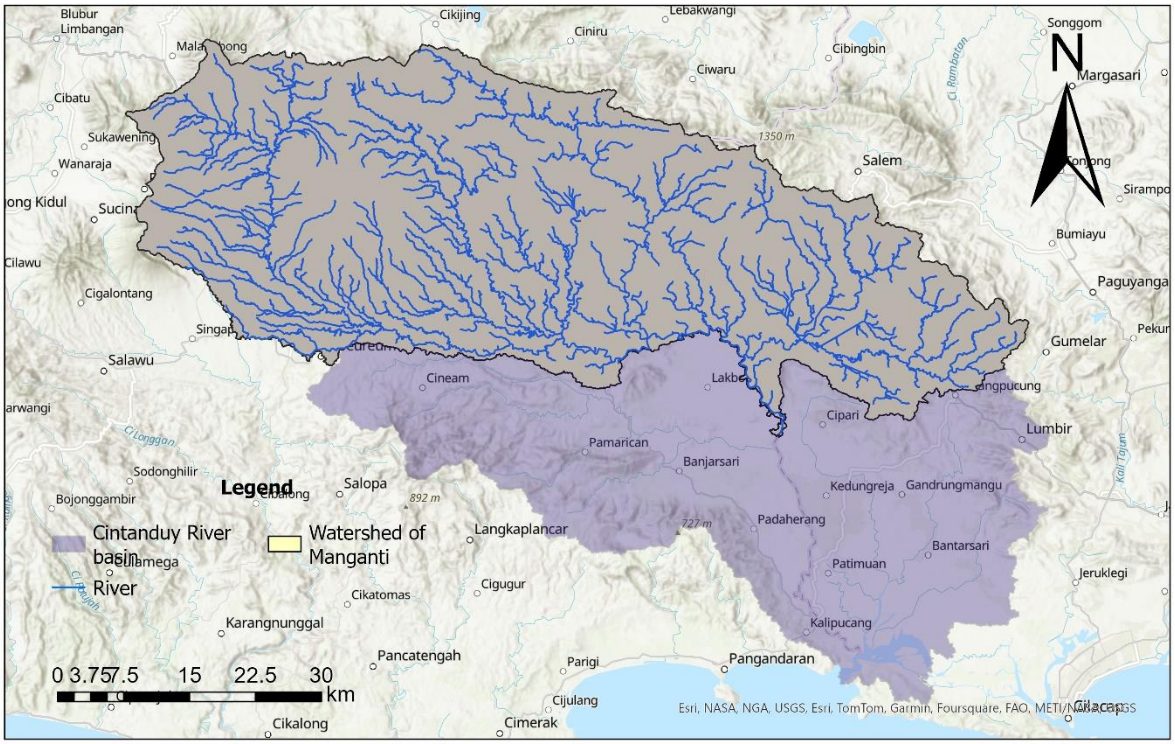

Figure 1: Manganti Dam Watershed

Figure 1 presents a detailed depiction of the Manganti Dam watershed, an expansive area covering 2,592 square kilometers. This vast watershed constitutes 60% of the entire Citanduy river basin, highlighting its significant role in the region's hydrology. The Citanduy river basin itself is a critical catchment area that supports a variety of ecological, agricultural, and human activities. The Manganti Dam, situated within this larger basin, is thus a key component in managing the water resources of a substantial portion of the catchment.

Data and Methodology

Data

In the realm of hydrological and hydraulic modeling, particularly in the context of flood risk management and water resources, the utilization of accurate and high-resolution historical data is paramount. Our study harnesses the Global Satellite Mapping of Precipitation (GSMaP) data, which offers enhanced spatial resolution with a grid size of 10 km x 10 km. This data is meticulously collected from the Japan Aerospace Exploration Agency (JAXA), ensuring a robust dataset for our analysis. The dashboard displaying this data is illustrated in Figure 2 of our documentation.

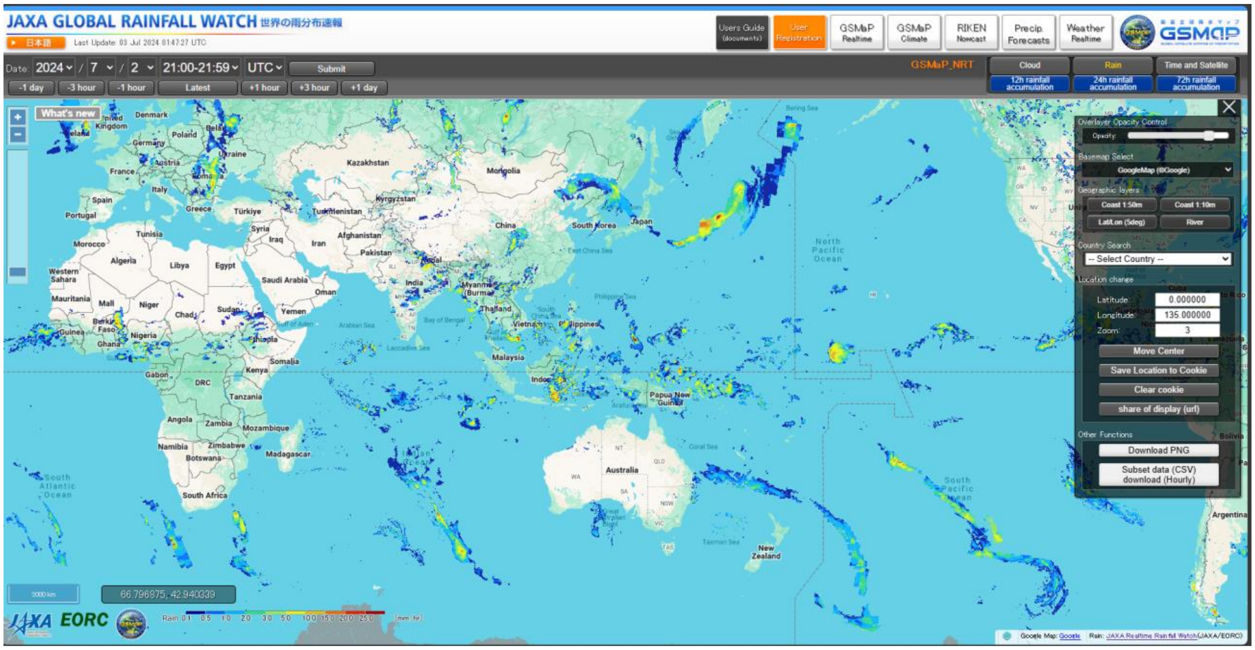

Figure 2: Dashboard of the GSMaP website

The GSMaP data boasts a spatial-temporal resolution of one hour, providing us with a granular view of precipitation patterns. Figure 3 further delineates an example of GSMaP rainfall data over Indonesia, showcasing the intricate details captured by this method. In our study, we have automated the collection process of GSMaP data specifically for the Indonesian region, streamlining the acquisition of this vital information.

Complementing the rainfall data, we also incorporate evaporation data from the Reanalysis Data ERA5. This dataset is renowned for its comprehensive coverage and reliability, spanning from 1998 to the present. The ERA5 data, coupled with the GSMaP rainfall data, forms a foundational component of our study, enabling us to conduct a thorough analysis of hydrological patterns and trends. This dual dataset approach empowers us to develop more accurate models for predicting and managing flood risks, ultimately aiding in the formulation of effective climate change adaptation strategies and irrigation optimization techniques. By leveraging these datasets, we aim to enhance our understanding of water resource dynamics and contribute to the resilience of communities against the challenges posed by extreme weather events.

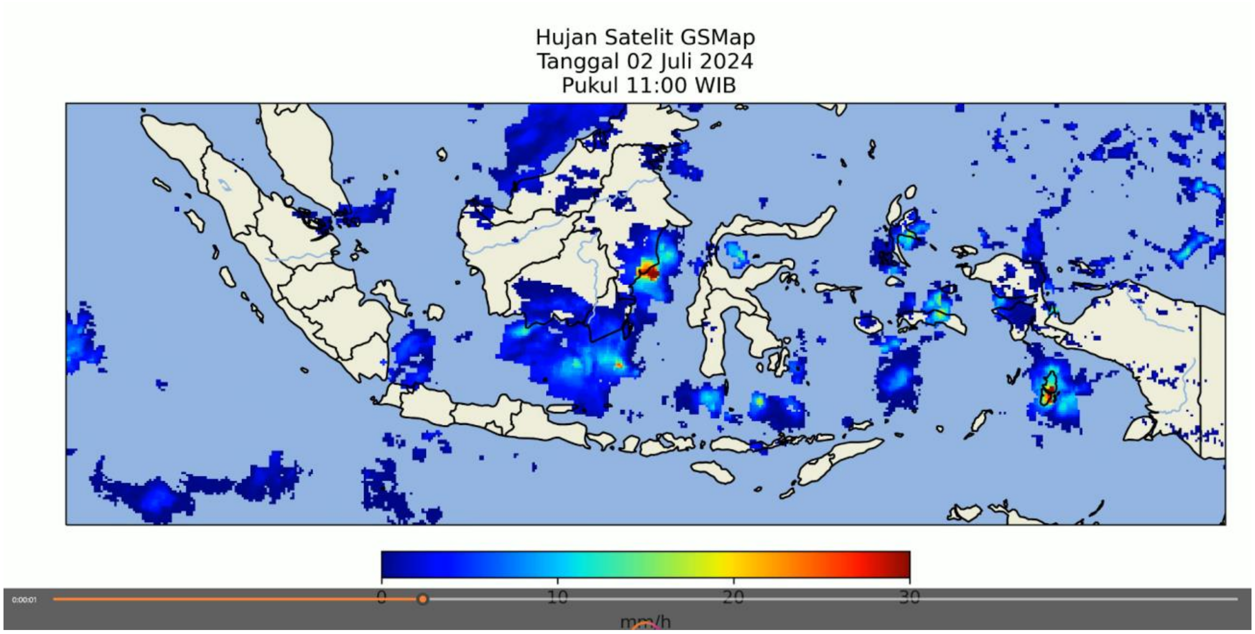

Figure 3: Example of GSMaP Data Covering the Indonesian Region

In the intricate field of hydro-meteorological forecasting, the selection of reliable and forward-looking data sources is crucial for predicting future weather patterns, especially in the context of climate change and its impact on water resources. Our study employs forecasting data from the European Centre for Medium-Range Weather Forecasts (ECMWF), which offers projections for evaporation and precipitation up to six months into the future. This data is not static; it undergoes monthly updates to ensure the most current and accurate forecasts are available. The ECMWF dataset is extensive, comprising 51 ensemble members, each representing a possible future state. This ensemble approach allows us to generate a comprehensive hydrograph for the upcoming six months, providing a spectrum of potential outcomes.

The user interface for accessing this data is depicted in Figure 4, showcasing the dashboard that facilitates the selection of datasets. While the ECMWF is our primary choice, the platform offers versatility by including other predictive models from reputable institutions such as the UK Met Office, Japan Meteorological Agency (JMA), and the National Centers for Environmental Prediction (NCEP). The decision to utilize ECMWF data is further reinforced by its adoption by the Badan Meteorologi, Klimatologi, dan Geofisika (BMKG), Indonesia's meteorological agency, which relies on it for official weather forecasting.
The rationale behind our preference for ECMWF data is rooted in its proven accuracy and the agency's reputation for providing high-quality weather predictions. By integrating ECMWF's forecasts into our study, we aim to enhance our predictive models for evaporation and precipitation, which are vital components in assessing water balance, planning irrigation schedules, and managing flood risks. This forward-looking data, when analyzed alongside historical records, enables us to construct a more dynamic and responsive framework for water resource management, ensuring that we are better equipped to handle the uncertainties posed by a changing climate.

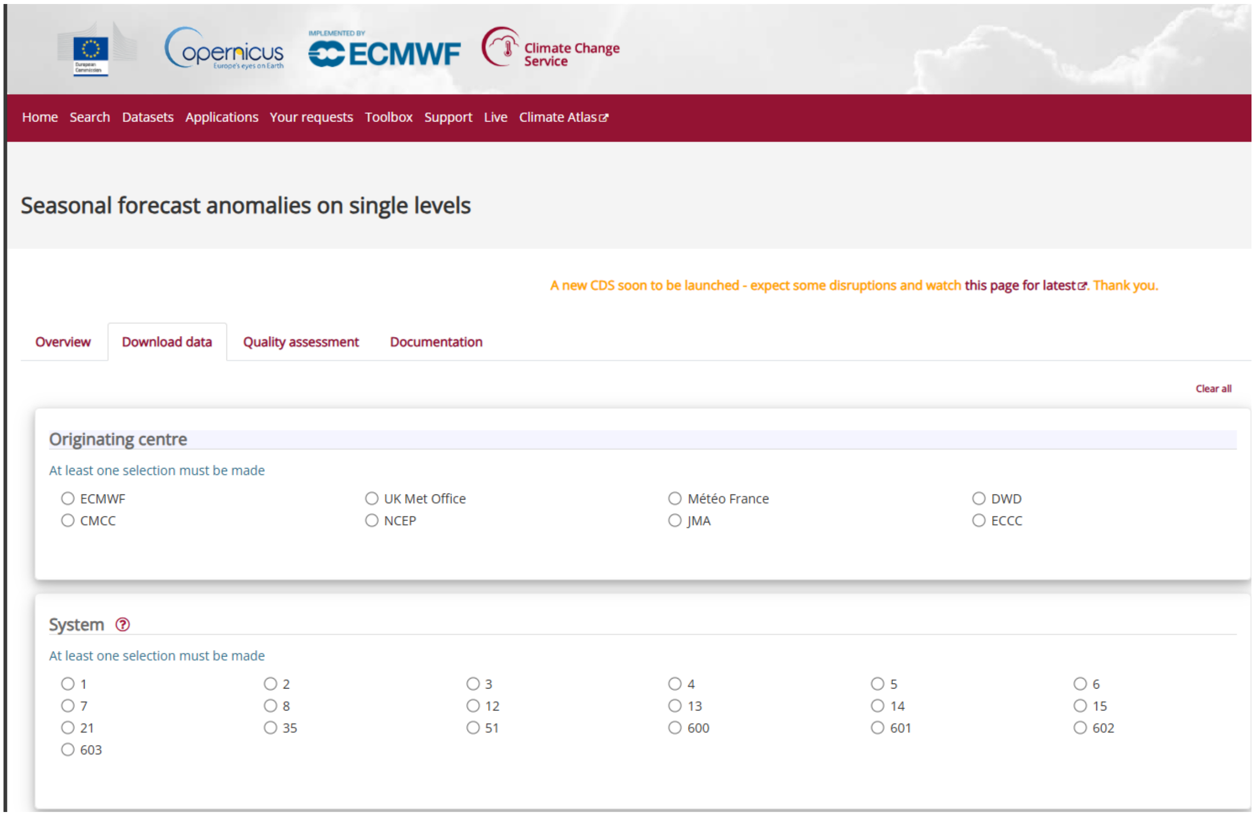

Figure 4: ECMWF Dashboard Website

Methodology

The Principle of Forecast Modeling

Our forecast model's conceptual framework demonstrates the complexity of contemporary hydrological research. Figure 5 shows how our approach melds historical data with predictive forecasts to form a sturdy model capable of handling climate variability's complexities. This process isn't just theoretical—it's a useful instrument that weaves together historical weather data and potential future scenarios.

Central to our model is the rainfall-runoff simulation, which converts precipitation into streamflow. This dynamic model adapts to new data. Incorporating 51 ensemble datasets brings realism to our predictions by recognizing natural uncertainties. These datasets aren't mere speculations; they are scientifically robust scenarios offering a spectrum of possible outcomes.

Our examination of these datasets is thorough. It's not simply about examining figures; we delve into the narrative they convey. When we consider average, minimum, and maximum hydrograph values for the upcoming half-year, we're interpreting more than mere data – we're piecing together a story of potential future events. This storyline is vital for policymakers who depend on our predictive models to strategize and gear up for impending water-centric obstacles.

Our model goes beyond initial calculations. It undergoes a daily process of reanalysis and corrections. We adjust the previously simulated discharge based on the real measurements of rainfall and evaporation from the day before. This isn't just a minor adjustment; it's a recalibration to maintain the accuracy and pertinence of our model.

The cyclical nature of our research is essential. With each day bringing in new information, our model adjusts accordingly, providing an updated prediction akin to the most recent meteorological update. This constant rejuvenation of our predictions guarantees that our model remains not as a mere historical artifact but rather as a progressive window into what lies ahead. It's this perpetual pattern of testing, refining, and evolving that turns our forecasting approach from a theoretical construct into an actual tool—one that equips us to confront future unpredictability with assuredness and precision.

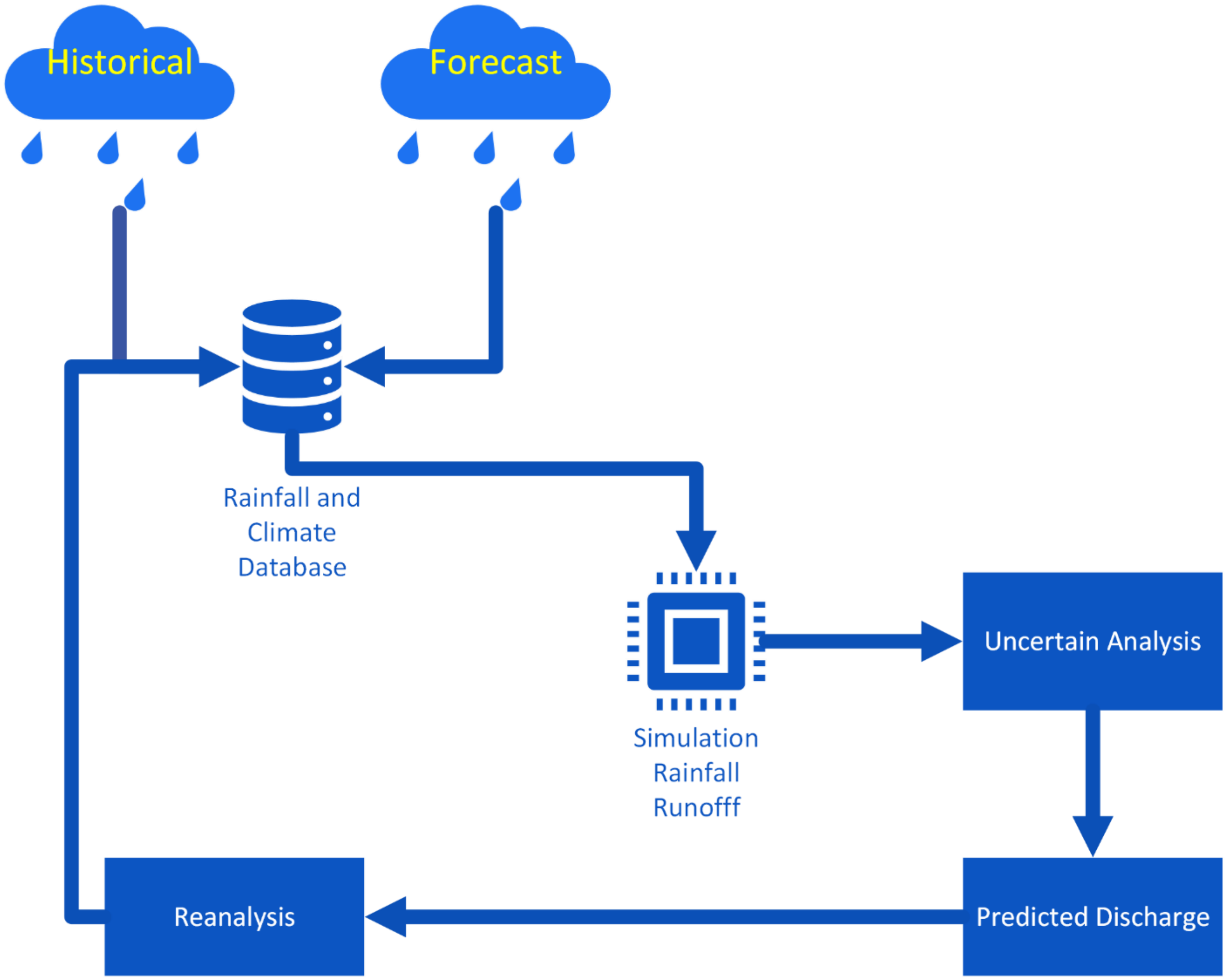

Figure 5: Forecasting Model Flowchart

Rainfall-Runoff Model

The rainfall-runoff model is a sophisticated tool in hydrological studies, designed to simulate the complex process of how rainfall translates into runoff within a watershed. This model is bifurcated into two primary components: the processes within the subbasin and the flow routing. The subbasin process is encapsulated by the conceptual tank model, which is a multi-layered representation of the land's hydrological response to precipitation. This model posits that the land is composed of four distinct layers, each corresponding to a different type of flow. As depicted in Figure 6, the conceptual model of the tank model delineates these layers with clarity.

The first layer represents the surface and sub-surface flow, which are the initial responses to rainfall. Water that does not infiltrate stays on the surface, leading to surface flow, while some water moves laterally just below the surface, creating sub-surface flow. The second layer, or tank, simulates the intermediate flow. This layer accounts for the water that infiltrates deeper into the soil but is still above the water table.

Moving further down, the third layer is responsible for the sub-base flow, which is the movement of water just above the bedrock. This layer captures the slow movement of water that has infiltrated past the root zone. Finally, the fourth layer represents the base flow, which is the water that reaches the water table and contributes to the streamflow during dry periods.

Each of these layers is characterized by different hydrological behaviors and response times to rainfall events. The tank model provides a framework for understanding how different soil layers and geological structures affect the movement of water from the moment it hits the ground to when it becomes part of a stream or river..

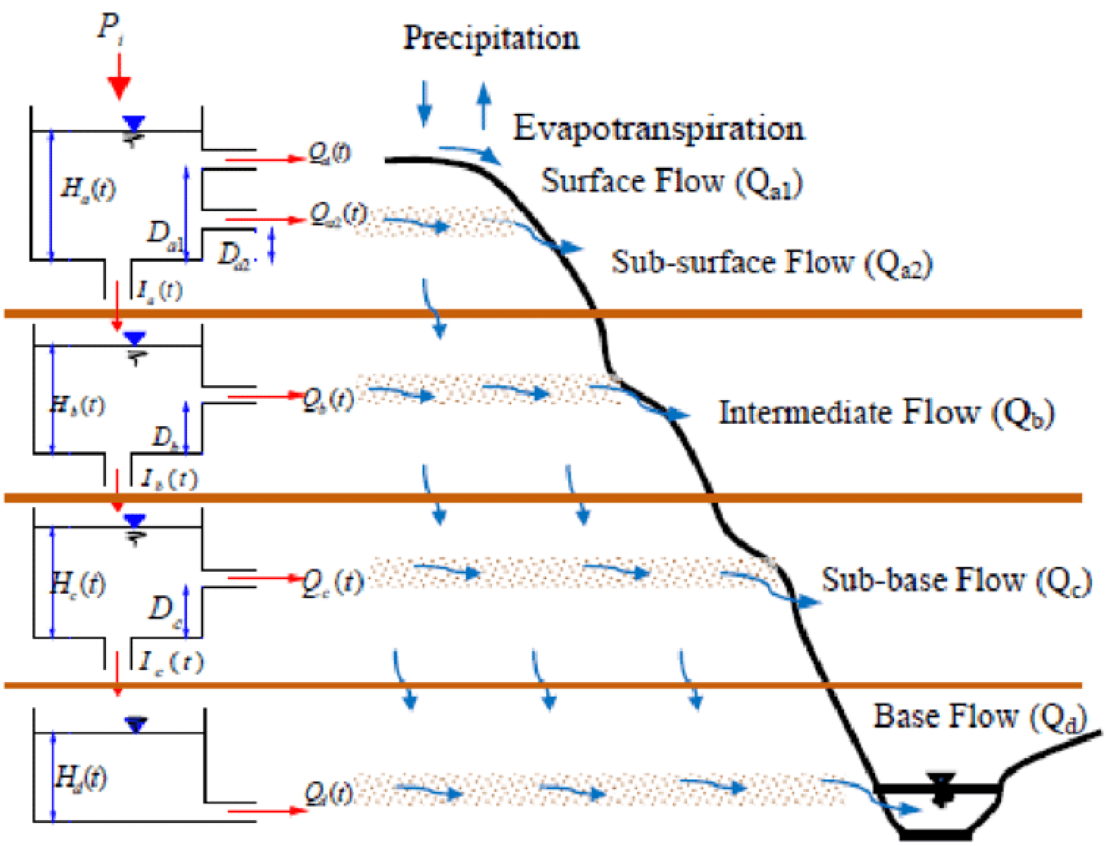

Figure 6: Schematic representation of the tank model

Flow routing, the second part of the model, involves the movement of water from upstream to downstream sub-basins. This process is governed by the **kinematic wave equation** and the **continuity equation**, which ensure that the discharge from the subbasin processes is accurately translated into lateral inflow for each sub-basin. The equations used are:

- **Continuity Equation**:

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = 0$$

- **Momentum Equation**:

$$\frac{1}{A}\frac{\partial Q}{\partial t} + \frac{1}{A}\frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right) + g\frac{\partial y}{\partial x} - g(S_o - S_f) = 0$$

These equations are fundamental in predicting how water flows through the watershed, which is essential for effective water resource management and flood risk mitigation. The model's ability to simulate these processes helps in designing sustainable irrigation systems and developing strategies to adapt to the impacts of climate change on water availability. The continuous refinement of this model through the incorporation of new data ensures its relevance and accuracy in hydrological forecasting.

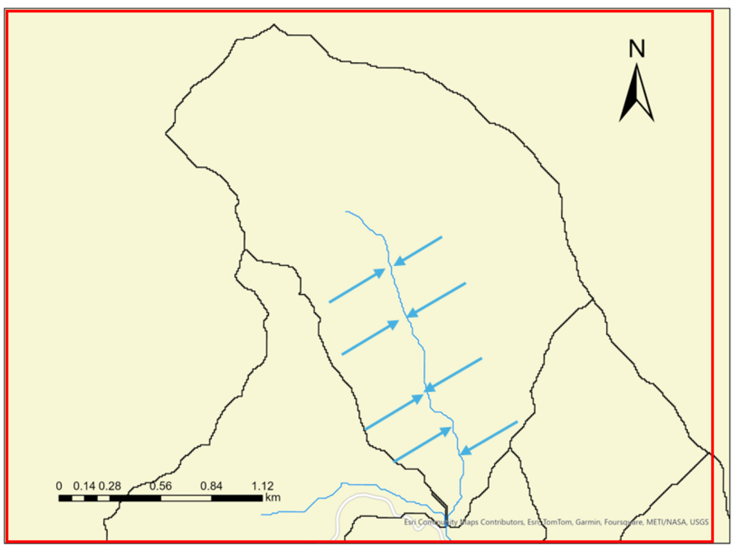

Figure 7: Lateral flow process into the river system

Results

Calibration

The hydrological model employed in this study is a semi-distributed model, which offers a balanced approach between the simplicity of lumped models and the complexity of fully distributed models. By dividing the Dam Mantan watershed into 734 sub-watersheds, the model achieves a high level of spatial detail that is critical for accurate hydrological analysis. The sub-watersheds vary significantly in size, ranging from as small as 0.02 km^2 to as large as 22.07 km^2, as shown in Figure 8. This variation in size allows the model to capture the heterogeneity of the watershed's physical characteristics, such as land use, soil type, and topography.

The rationale behind delineating such a large number of sub-watersheds is to obtain a granular understanding of the Manganti Dam watershed. This granularity enables the model to simulate hydrological processes with greater precision, accounting for the unique conditions of each sub-watershed. As a result, the model can provide detailed insights into the flow patterns, water balance, and potential flood risks within the watershed.

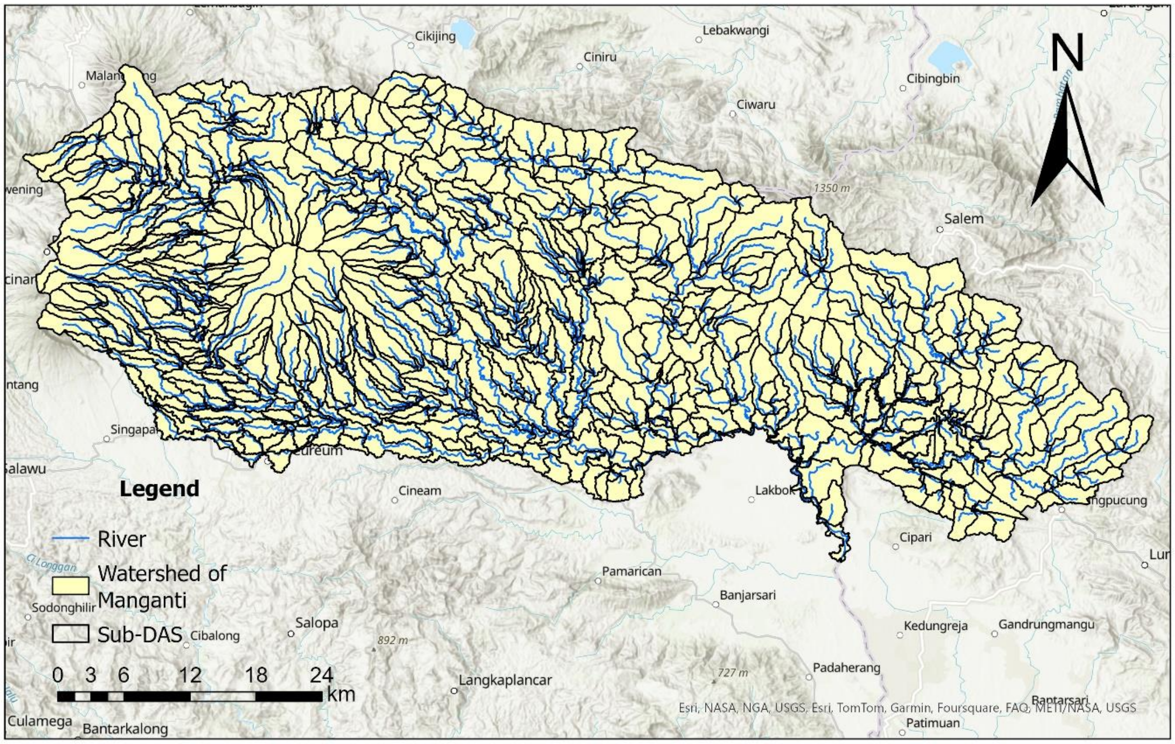

Figure 8: Delineation of the Sub-basin in the Manganti Dam Watershed

The calibration of the hydrological model is a meticulous two-part process that ensures the model accurately reflects the real-world conditions of the Manganti Dam watershed. The first part of the calibration process is conducted without considering the water extraction (taking factor) upstream of the Manganti Dam. This initial calibration is crucial as it establishes a baseline for the model's performance under undisturbed conditions.
During this phase, the parameters or coefficients of the tank model are carefully adjusted. These adjustments are made based on the type of land cover present within the watershed, as different land covers can significantly influence the hydrological response of the area. For instance, urban areas with impervious surfaces will have a different runoff pattern compared to forested areas with high infiltration rates. The parameters that are tuned might include factors such as the storage capacity of each layer in the tank model, infiltration rates, and evapotranspiration coefficients.
Table 1 in the study provides a detailed breakdown of the tank model parameters that are used, categorized by the type of land cover. This table is an essential reference for

understanding how each land cover type affects the model's parameters and, consequently, the simulation results.
Furthermore, the study includes an appendix that presents the distribution of land cover percentages for each sub-watershed. This distribution is critical for the calibration process as it informs the model of the spatial variability within the watershed. By incorporating this data, the model can more accurately simulate the hydrological processes on a sub-watershed level, taking into account the unique characteristics of each area.

Table 1: Model Parameters According to Land Cover

Model Parameter	Land cover							
	Badan Air	Belukar	Hutan	Ladang	Pemukiman	Perkebunan	Sawah	Tanah Terbuka
C2	0.15	0.65	0.2	0.75	0.8	0.65	0.7	0.65
C1	0.1	0.05	0.15	0.15	0.1	0.1	0.15	0.05
C0	0.7	0.25	0.6	0.1	0.1	0.2	0.2	0.25
H2	150	30	150	35	30	30	60	30
H1	90	15	90	20	15	15	20	15
SA	10	10	10	10	10	10	10	10
C3	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Cb	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
H3	10	10	10	10	10	10	10	10
SB	50	50	50	50	50	50	50	50
C4	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015
Cc	0.003	0.002	0.003	0.002	0.002	0.002	0.0025	0.002
H4	10	10	10	10	10	10	10	10
SC	600	600	600	600	600	600	600	600
C5	0.003	0.002	0.003	0.002	0.002	0.002	0.0025	0.002
SD	625	625	625	625	625	625	625	625

The results of the hydrological model, which simulates the conditions of the Manganti Dam watershed without accounting for water intake upstream shown Figure 9, are quantitatively assessed using the Kling-Gupta Efficiency (KGE) metric. This metric provides a holistic measure of the model's performance by combining correlation, variability, and bias components into a single value. The KGE value obtained from the simulation is 0.54, which indicates a moderate level of agreement between the observed data and the model's simulation.

Breaking down the KGE into its components:

- The Correlation component, with a value of 0.54, reflects the degree to which the simulated and observed data sets are linearly related. A value closer to 1 would indicate a perfect linear relationship, so this value suggests a moderate positive correlation.
- The Variability component (alpha), valued at 0.94, assesses the ratio of the simulated data's variability to that of the observed data. An alpha value of 1 would mean the model perfectly captures the observed variability. The obtained value being close to 1 suggests that the model is reasonably successful in simulating the natural variability of the system.

- The Bias component (beta), with a value of 1.18, measures the ratio of the average simulated values to the average observed values. A beta value of 1 would indicate no bias; the model's average output matches the observed average. The value greater than 1 indicates the model tends to overestimate the average discharge.

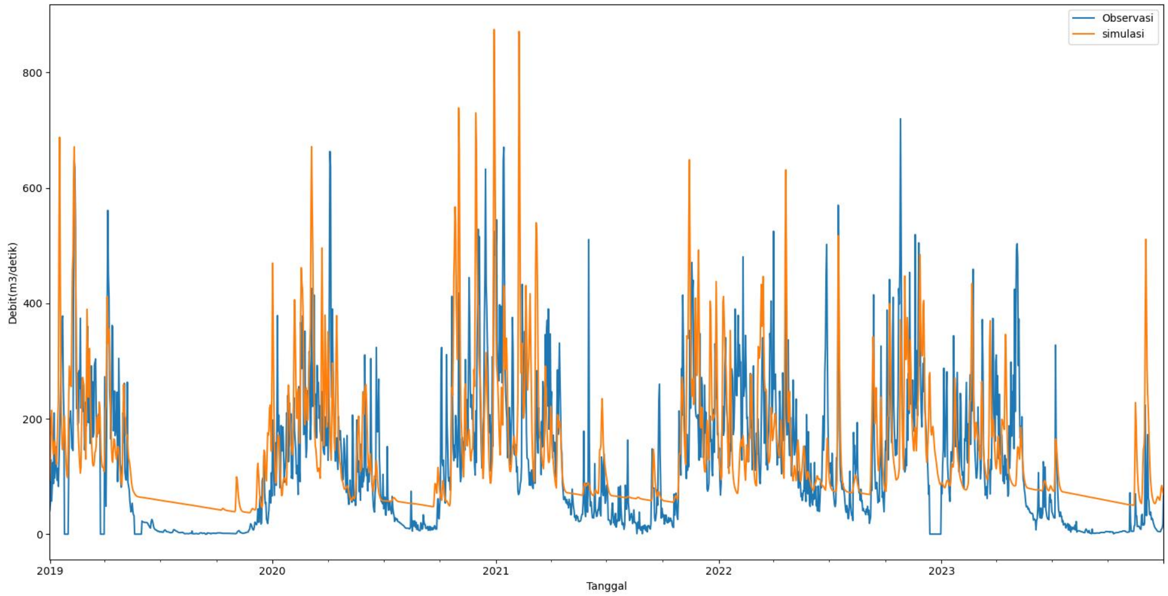

Figure 9: Contrast between actual observations and simulations without upstream water extraction

The hydrological model's results, incorporating the factor of water extraction upstream of the Manganti Dam watershed, provide a nuanced understanding of the watershed's behavior under the influence of human activities. KGE metric is employed to quantitatively evaluate the model's performance, and the results are presented in Figure 10.
The KGE value stands at 0.59, indicating a reasonable level of agreement between the model's simulations and the observed data. This value suggests that the model is fairly accurate in capturing the overall hydrological behavior of the watershed, despite the complexities introduced by water extraction activities.

Breaking down the KGE into its individual components:

- The Correlation component, with a value of 0.60, signifies a moderate positive linear relationship between the simulated and observed data. This indicates that the model's simulations tend to rise and fall in tandem with the actual observations, although not perfectly.
- The Variability component (alpha), at 0.97, is very close to the ideal value of 1. This implies that the model is highly capable of replicating the observed data's variability, which is crucial for understanding the range of possible hydrological responses within the watershed.
- The Bias component (beta), with a value of 0.99, shows that the model's average simulated output is almost equal to the observed average, indicating minimal bias. This near-perfect score suggests that the model neither systematically overestimates nor underestimates the observed data.

Overall, the KGE components reflect a hydrological model that is well-calibrated and sensitive to the impacts of water extraction on the watershed. The model's ability to maintain high accuracy in the presence of anthropogenic factors is indicative of its robustness and reliability. Such a model is invaluable for water resource managers and policymakers, as it provides a credible tool for forecasting and planning in the context of ongoing and future water usage within the Manganti Dam watershed. The insights gained from this model can guide sustainable water management practices and help in devising strategies to mitigate the impacts of water extraction on the watershed's health and resilience.

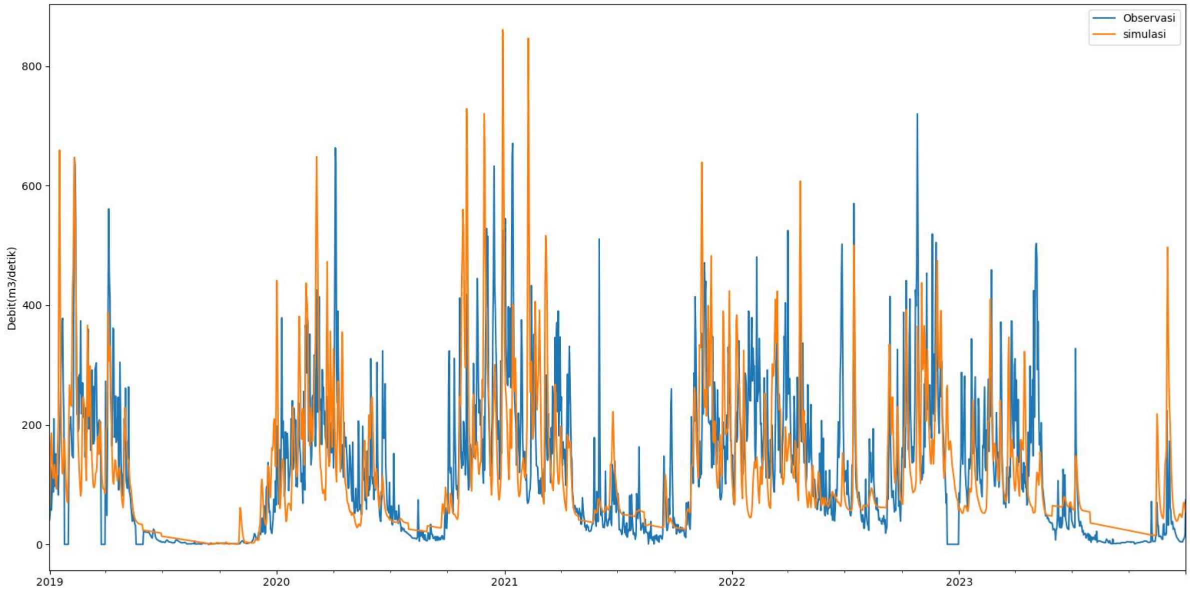

Figure 10: Contrast between actual observations and simulations with upstream water extraction

Validation

To validate the model, we used observational data from June 1st to June 19th, 2024. We compared this against the forecasted outflow at Manganti Dam. Among 51 datasets used, the simulation closely matched the observed minimum discharge as seen in Figure 11. The trend shows that the simulated results align well with actual observations. Nevertheless, there was a weaker correlation with the predicted maximum discharge values. Further work is needed to improve the accuracy of the model.

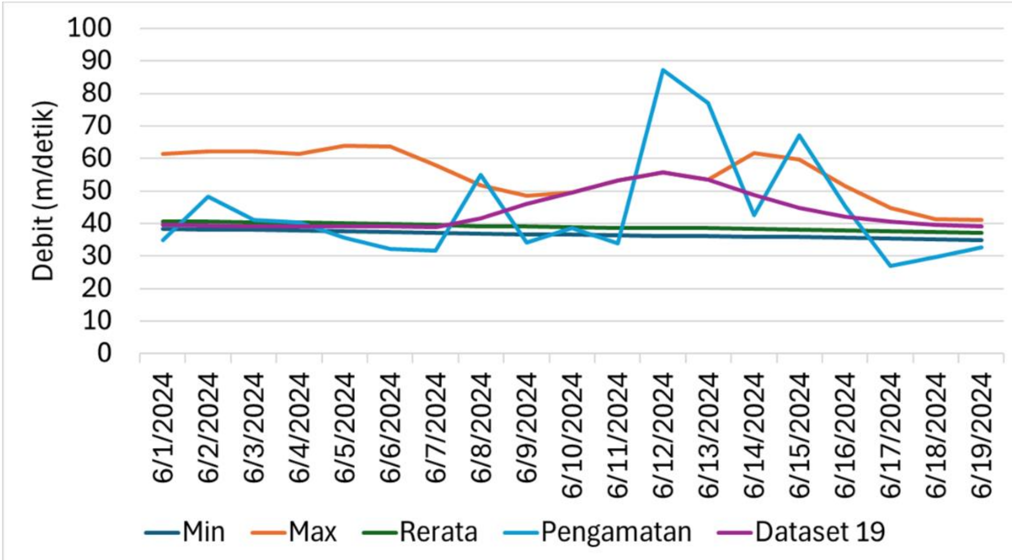

Figure 11: Comparison between observed and forecasted discharge data

Forecasting

The simulation results of this model will obtain hydrographs for the next 6 months as seen in Figure 12. These hydrographs consists of 51 datasets. From these results, the hydrograph values displayed in the maximum and minimum value hydrographs, interquartile range quartile 1 and quartile 3, as well as the average value of the discharge and the median discharge hydrograph will be obtained. The purpose of this simulation is to provide a probabilistic forecast of the expected discharge patterns at the Manganti Dam, taking into account the effects of water extraction and climate variability. The significance of this simulation is that it can help water managers and policymakers to anticipate and prepare for possible water shortages or excesses, and to optimize the allocation and distribution of water resources within the watershed.

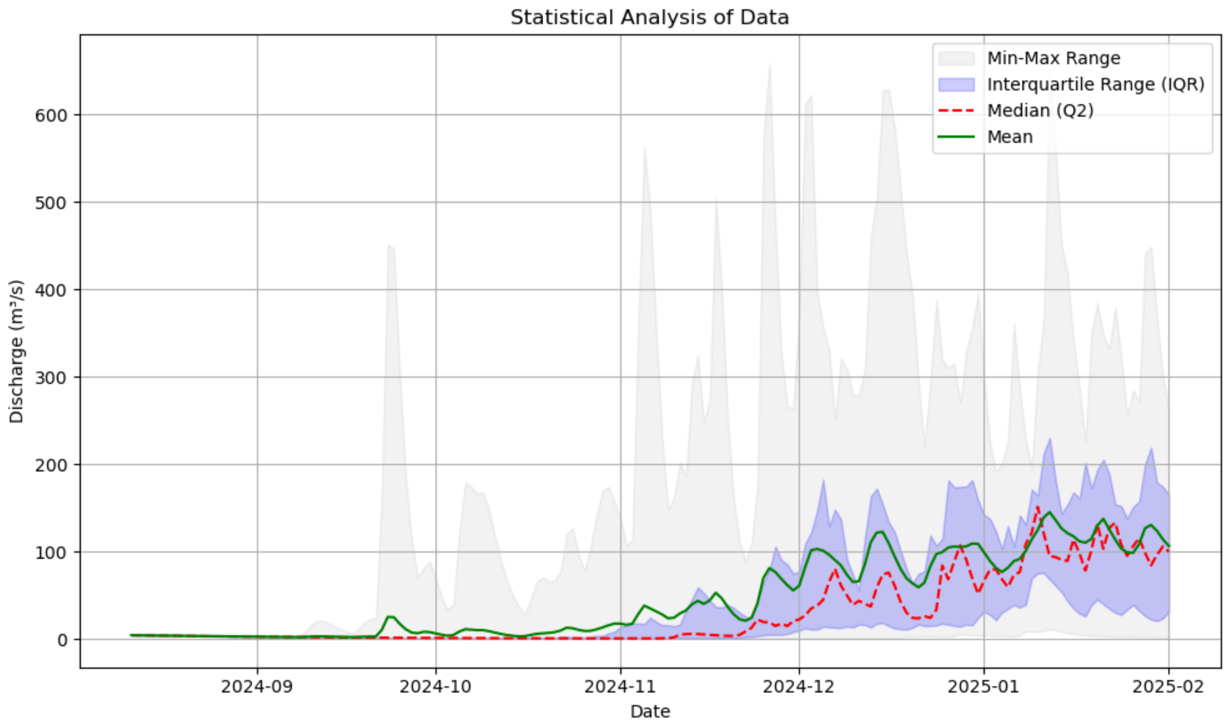

Figure 12: Predictive simulation outcomes for discharge over the following six months