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Analysis of Dependable Flow in the Brantas Watershed using *Google Earth Engine*

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Abstract

Dependable flow analysis is crucial for water resource management, such as in the Brantas River Basin, but is often hindered by the limitations of conventional observation data (AWLR). This research demonstrates an alternative methodology by integrating the Google Earth Engine (GEE) platform with the F.J. Mock hydrological model to estimate dependable flow, using a quantitative descriptive approach in the Brantas River Basin, Blitar Regency (area 1588.79 km²). The research methodology includes the acquisition of CHIRPS satellite rainfall data (2022–2024 period) via GEE and climatological data from BMKG. Potential Evapotranspiration (ETo) was calculated using the Modified Penman Method. Both rainfall (P) and ETo data were used as inputs for the F.J. Mock model to simulate monthly discharge (Q_{model}), which was then analyzed using a Flow Duration Curve (FDC) with the Weibull formula. The results successfully identified the dependable flow values: Q70 = 0.65 m³/s, Q80 = 0.19 m³/s, and Q90 = 0.07 m³/s. This study concludes that the integration of GEE for data acquisition and the F.J. Mock model for hydrological simulation provides an effective, efficient, and technology-based alternative to overcome conventional data limitations in water resource planning.

Keywords: *Brantas River Basin, CHIRPS, Dependable Flow, F.J. Mock Method, Google Earth Engine (GEE)*

1. Introduction

Water availability is a fundamental foundation for social, economic, and ecological sustainability in various parts of the world. In the context of global climate change and increasing anthropogenic pressures, water resource management faces increasingly complex challenges, especially in maintaining the balance between human needs and environmental preservation [1]. One important approach in water resource management is the analysis of dependable flow, which serves as a basis for irrigation planning, raw water supply, and the regulation of ecological flows in a river basin (watershed). (such as $Q_{70} = 0.65$ m^3/s, $Q_{80} = 0.19$ m^3/s, and $Q_{90} = 0.07$ m^3/s

In Indonesia, the issue of water availability and distribution is becoming more urgent, along with increasing demand due to population growth and industrial activities. The Brantas River Basin, as one of the national strategic river basins on the island of Java, plays a vital role in supporting the lives of more than 15 million people and serves as a centre for agricultural and industrial activities in East Java Province. However, this area faces high water resource pressure, characterized by water use conflicts, environmental degradation, seasonal floods, and recurring drought threats. These conditions affirm the importance of accurately determining dependable flow as a basis for decision-making in fair and sustainable water resource management.

Conventionally, the calculation of dependable flow relies on long-term observation data from Automatic Water Level Recorders (AWLR). This approach is often constrained by the limited number of representative observation stations, the presence of missing data, and time-consuming collection and validation processes. These limitations lead to a low availability of consistent hydrological data across the entire river basin, thereby hindering evidence-based planning.

To overcome these observational data limitations, the development of cloud computing technology and the availability of global climate data open new opportunities. Google Earth Engine (GEE), as a cloud-based geospatial analysis platform, enables the efficient processing of large-scale data with direct access to a petabyte-scale archive of satellite data and global climate models like ERA5-Land. Through the integration of daily runoff data, which represents combined surface and subsurface flow, GEE can be used to construct a Flow Duration Curve (FDC) and estimate dependable flow quickly and consistently across various regions.

Based on this background, this research aims to demonstrate the application of Google Earth Engine in estimating the dependable flow of the Brantas River Basin using runoff data from the ERA5-Land model. The analysis is conducted on time-series data over 3 years (2021–2024) to evaluate the potential of this method as an alternative and a complement to field observation data in supporting adaptive, technology-based water resource management.

2. Literature Review

Dependable flow analysis is a crucial component in the planning and management of water resources, whether for irrigation, raw water supply, or electric power. However, this analysis conventionally faces challenges due to the limitations of observed discharge data from Automatic Water Level Recorders (AWLR). These limitations include the availability of short historical datasets, missing data, or an unrepresentative distribution of gauging stations [2, 3].

To overcome these observational data limitations, an approach has been developed that utilizes rainfall-runoff models with satellite-based precipitation data as input. In Indonesia, one common hydrological model used to simulate the water balance and estimate discharge is the F.J. Mock Method. Another is the NRECA method, which was applied by researchers in the Rejoso Watershed, a simpler conceptual model (often called a lumped model). This model does not break down physical processes in as much detail as the F.J. Mock method, but instead uses specific indices and parameters to partition rainfall into runoff. This method is an alternative to the F.J. Mock method and is considered suitable for application in regions with low rainfall intensity and in catchments that maintain flow even after rainfall ceases [4]. Although the NRECA method requires a number of more complex input parameters compared to other methods, its flexibility in adapting to local conditions makes it relevant for various regions with limited hydrological data.

Relevant research applying this approach was conducted by researchers in the Gembong Watershed, Pasuruan Regency. That research focused on converting rainfall into discharge using the F.J. Mock Method by utilizing rainfall data from the GPM (Global Precipitation Measurement) satellite. The main strength of the Gembong Watershed research lies in its in-depth model calibration and validation process. They used a Genetic Algorithm for model parameter optimization and compared it with observed discharge data (AWLR), achieving "very good" model performance in the calibration phase (NSE 0.998) and "satisfactory" in the validation phase (NSE 0.5124). This research successfully proved that calibrated GPM satellite data can be used for accurate dependable flow estimation [5].

Although the research conducted in the Gembong Watershed demonstrated the validity of using satellite data (GPM) through comprehensive calibration, the process still relied on conventional data processing and parameter optimization (e.g., using Solver in Microsoft Excel). Another challenge emerging in modern hydrology is the efficiency in the acquisition and processing of global climate data, which often exists at a petabyte scale.

Therefore, this research will focus on addressing this gap. This study will adopt the F.J. Mock model, which has been proven valid, but will integrate it with a cloud computing platform (such as Google Earth Engine) to automate data acquisition and processing. The objective is to generate a methodology for dependable flow estimation that is not only hydrologically accurate but also far more efficient in processing large-scale data.

3. Methods

3.1. Type of Research

This research uses a quantitative descriptive approach. It is called quantitative because the data collected, processed, and analyzed are in the form of statistical figures, such as rainfall data (mm), climatological data (temperature, humidity, duration of sunshine, wind speed), and also discharge (m^3/second).

·3.2. Research Location

The location of this research is the Brantas River Basin (Watershed) in Blitar Regency, which can be seen at Figure 1.

Fig 1. Brantas Watershed Research Location, Blitar Regency

3.3. Data Collection Methods

The data used by the researcher are secondary data compiled through several specific, structured methods or steps. Secondary data is data obtained or collected by the researcher indirectly. This is data that has previously been collected, processed, and published by other parties (government agencies, research institutions, other researchers, or organizations) for purposes that may be different, but are still relevant to be reused in the research. The following are some of the secondary data used in this research:

a. Climatological Data
b. Rainfall Data using satellites from Google Earth Engine

Table 1. Climatological Data

No	Climatological Data
1	Temperature (°C)
2	Humidity (%)
3	Long Exposure (Hours)
4	Wind Speed (km/h)

3.3.1 Dependable Flow

Dependable flow is the minimum stream discharge available to meet water needs, determined based on a calculated risk of failure. This risk is typically quantified as a probability of exceedance (e.g., Q80, meaning the flow is equal or exceeded 80% of the time). In planning any water project, engineers must first quantify this dependable flow to determine the planning discharge magnitude of flow expected to be consistently available in the river. This value is foundational to engineering design and ensuring the risk of water shortage is managed to an acceptable level. This quantification is rooted in understanding the hydrological process, which is simply the relationship between its core elements: the input, namely rain (precipitation); the catchment process; and the output, namely in the form of flow. Therefore, the relationship of rainfall-runoff is an essential problem in hydrology and represents the fundamental component in the process of evaluating water resources [6].

3.3.2 Evapotranspiration

Evapotranspiration (ET) is a critical link in the hydrological cycle, representing the combined transfer of water to the atmosphere from evaporation and transpiration. Evaporation occurs on all moist surfaces, such as water bodies and bare soil, while transpiration is the biophysical release of water vapor from plants. Although ocean evaporation is the largest global flux, terrestrial ET is a key driver of regional water balances. Quantifying ET is complex, so it is typically calculated using theoretical approaches. This methodology, for example, calculates Potential Evapotranspiration (ETo) using the Modified Penman method, which integrates energy and aerodynamic principles [7]:

$$ETo = C \times (W \times R_n) + \left((1 - W) \times f(U) \times (\epsilon\gamma - \epsilon d)\right) \tag{1}$$

Where ETo is the Potential Evapotranspiration; C is a calculation constant for the Modified Penman method; W is a weighting factor dependent on air temperature; Rn is the net radiation, obtained from the difference between net shortwave radiation (Rns) and net longwave radiation (Rn1); (1 - W) is the complementary weighting factor for the aerodynamic component; f(U) is a function representing the effect of wind speed; $\varepsilon\gamma$ is the saturation vapor pressure, determined based on air temperature; and εd is the actual vapor pressure, which is calculated based on saturation vapor pressure ($\varepsilon\gamma$) and relative humidity.

3.3.3 Flow Duration Curve / Rating Curve

For the water availability assessment, the Flow Duration Curve (FDC) method was employed. This procedure involved ranking the historical discharge dataset (e.g., daily or monthly) in descending order. Subsequently, an exceedance probability was assigned to each data point using the Weibull plotting position formula. The dependable flow was then identified from the resulting curve corresponding to a predefined probability of exceedance (e.g., 80% or 90%).

$$P(X \geq x) = \frac{m}{n+1} 100\% \tag{2}$$

Where, $P(X \geq x)$ = the probability of the occurrence of variable X (discharge) being equal to or greater than x m^3/s (the percentage probability), m = the data rating, the order number of the discharge n = the amount of data, the number of data X = the series data discharge, the dependable flow = the reliable discharge when the probability matches the allotment of the source of clean water, and $P(X \geq Q90\%) = 0.9$ [8].

3.3.4 F.J. Mock Method

The hydrological process can be simply described by the relationship between elements of input, process, and output. In the F.J. Mock Method, the primary input is precipitation (P). The process is then simulated as a detailed water balance model. This begins by calculating the water available at the surface (As) by subtracting evapotranspiration (Et) from precipitation:

$$\mathrm{A_s} = \mathrm{P} - \mathrm{E_t} \tag{3}$$

This available water (As) then contributes to soil storage, with any excess becoming water surplus (WS). This surplus is split into direct runoff (DR) and infiltration (I). The infiltrated water (I) contributes to base flow (BF) after accounting for changes in groundwater storage (DVn). The resulting output is the total river flow, which is first calculated as the sum of these components, called Total Runoff (Tro):

$$T_{ro} = BF + DR \tag{4}$$

This T_{ro} value (in mm) is finally converted into the output discharge (Q_{model} in m^3/s) using the catchment area (Watershed Area) and time conversion. This rainfall-runoff relationship is an important problem in hydrology and is the most fundamental component in the process of evaluating water resources [9].

3.3.5 Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a global precipitation dataset developed by the Climate Hazards Group at the University of California, Santa Barbara (UCSB), in collaboration with the U.S. Geological Survey (USGS) and the USAID Famine Early Warning Systems Network (FEWS NET). This dataset provides data at a high spatial resolution of 0.05° (approximately 5 km) and offers extensive temporal coverage from 1981 to near real-time[2]. The primary advantage of CHIRPS lies in its blended methodology, which combines *in-situ* observation data from ground stations with infrared satellite-based estimates. This approach yields more representative precipitation estimates, particularly in regions with limited meteorological observation networks. Access and processing of CHIRPS data can be performed using the *Google Earth Engine* (GEE) cloud computing platform. GEE can be utilized to extract precipitation time-series data for specific boundaries, which can then serve as a primary input for hydrological analyses, such as the F.J. Mock Method [10].

3.4. Analysis Data

Research must be conducted systematically with clear and structured phases to yield outputs that align with the intended objectives. To achieve this, the study is divided into several main, interrelated stages, each supporting the attainment of optimal research outcomes. The first stage is preparation and literature review. This phase involves deepening the understanding of the research topic, particularly concerning the concept of dependable flow, the F.J. Mock hydrological simulation method, and the utilization of CHIRPS satellite rainfall data through the Google Earth Engine (GEE) platform. This stage also includes problem formulation, defining the study area boundaries (Area of Interest/AOI), and gathering related climatological data required for evapotranspiration calculations. The second stage is secondary data collection. Data collection in this research consists of two main components. The first component is rainfall data, obtained by accessing and extracting time-series data from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) satellite via the GEE platform for a specified time range. The second component is climatological data, which includes parameters such as air temperature, humidity, sunshine duration, and wind speed, downloaded from official sources like BMKG. After the data is collected, the research proceeds to the data processing and analysis stage. This stage begins with the calculation of Potential Evapotranspiration (ETo) using the Modified Penman Method based on the collected climatological data. Subsequently, the rainfall data (P) from CHIRPS and the ETo data are used as inputs for monthly discharge simulation using the F.J. Mock Method. The F.J. Mock model simulates the water balance, including infiltration, soil storage, water surplus, direct runoff, and base flow, to generate a time-series of modelled discharge (Q_{model}). The resulting (Q_{model}) data is then analyzed to create a Flow Duration Curve (FDC). The FDC is constructed by sorting the discharge data from largest to smallest and calculating its probability using the Weibull formula, which is then used to extract dependable flow values (e.g., Q_{70}, Q_{80}, and Q_{90}).

The final stage is drawing conclusions, where the processed and analyzed data are summarized to answer the research problems and objectives, namely determining the estimated dependable flow values of the Brantas River Basin with the GEE innovation. All these stages are designed to be integrated and provide a clear workflow, so the research process can run effectively and efficiently. A visualization of these research stages can be presented in the form of a flowchart to provide a clearer picture of the flow and processes undertaken in this research.

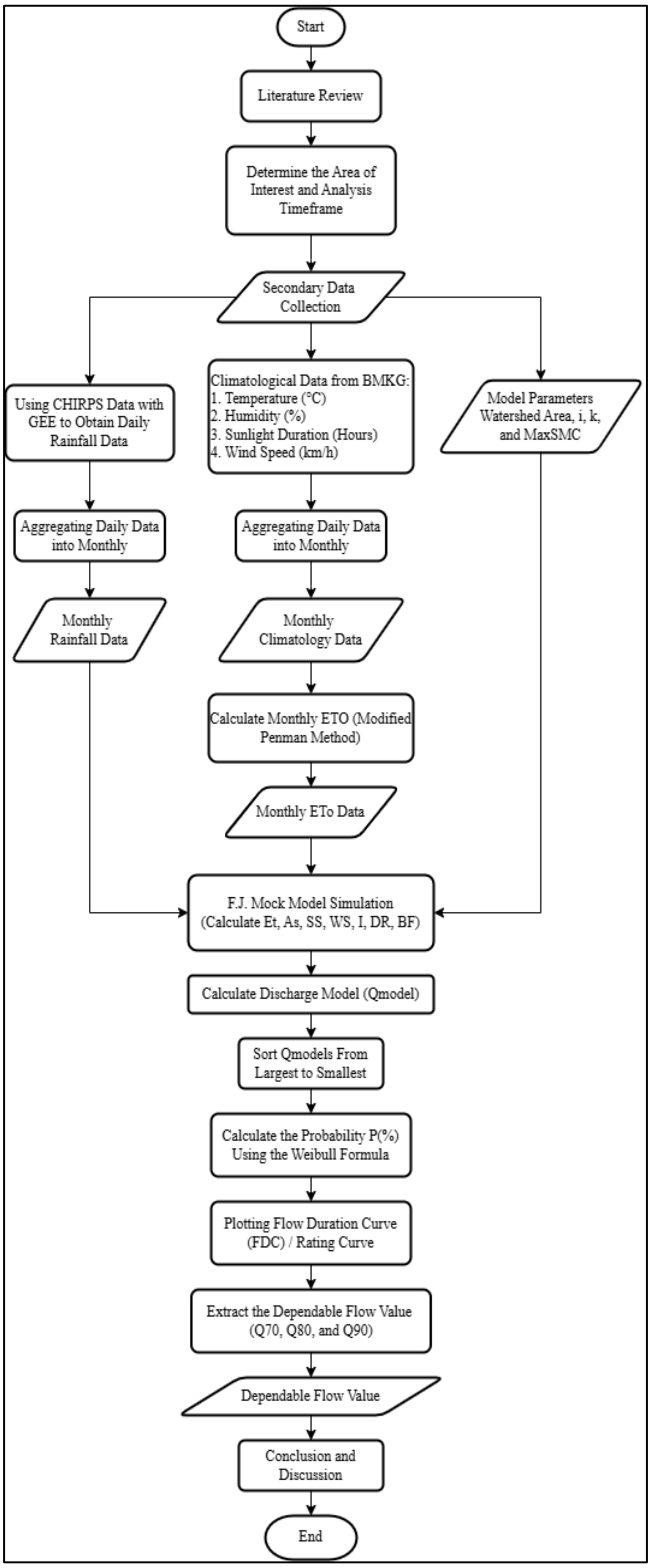
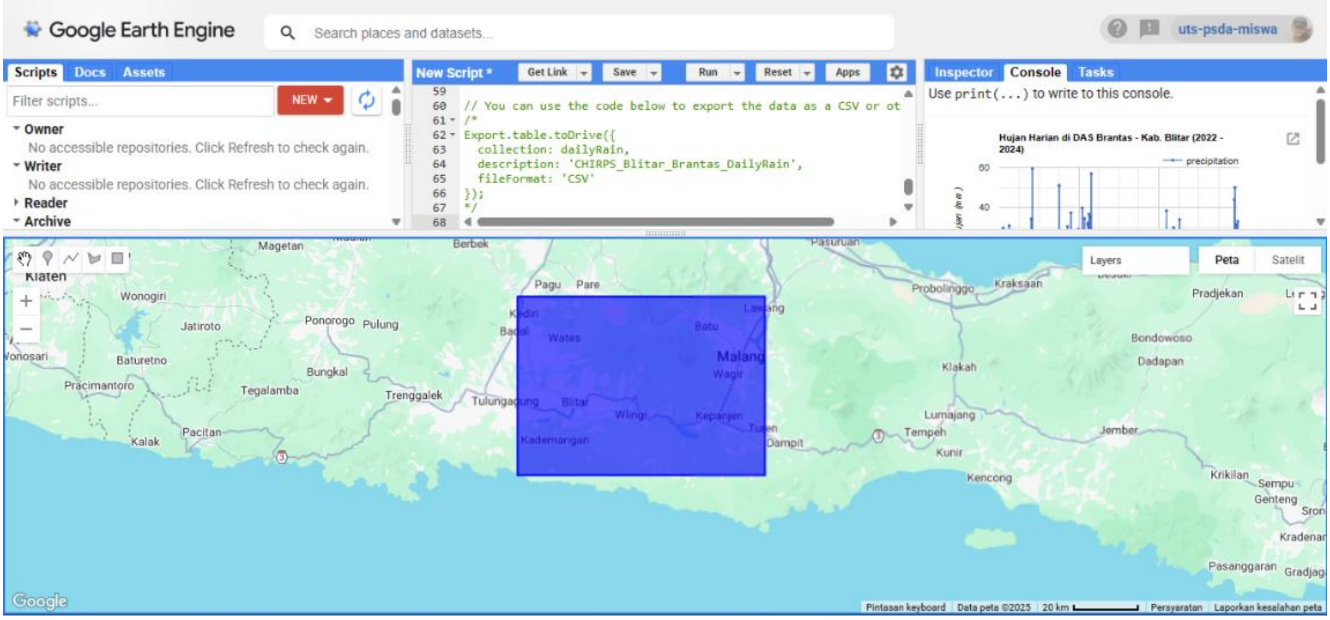


Fig 2. Data Processing Flowchart

4. Result and Discussion

Data processing in this research was carried out through systematic stages to analyze climatological data and rainfall data using the BMKG website and also GEE. The first stage was the acquisition of rainfall data using the GEE cloud computing platform. This process began with account registration and the creation of a new project within GEE. Next, the study area, in this case, Blitar Regency, was defined in the GEE code editor by inputting coordinate data. The regional coordinates were converted using external tools if necessary. The GEE script was then executed to process and extract daily rainfall data from the CHIRPS dataset. The result of this process was daily rainfall time-series data in CSV format, ready for further analysis.



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```
// You can use the code below to export the data as a CSV or ot
/*
Export.table.toDrive({
  collection: dailyRain,
  description: 'CHIRPS_Blitar_Brantas_DailyRain',
  fileFormat: 'CSV'
});
*/
```

Use print(...) to write to this console.

Fig 3. Run results from SCRIPT for Blitar Regency area using GEE

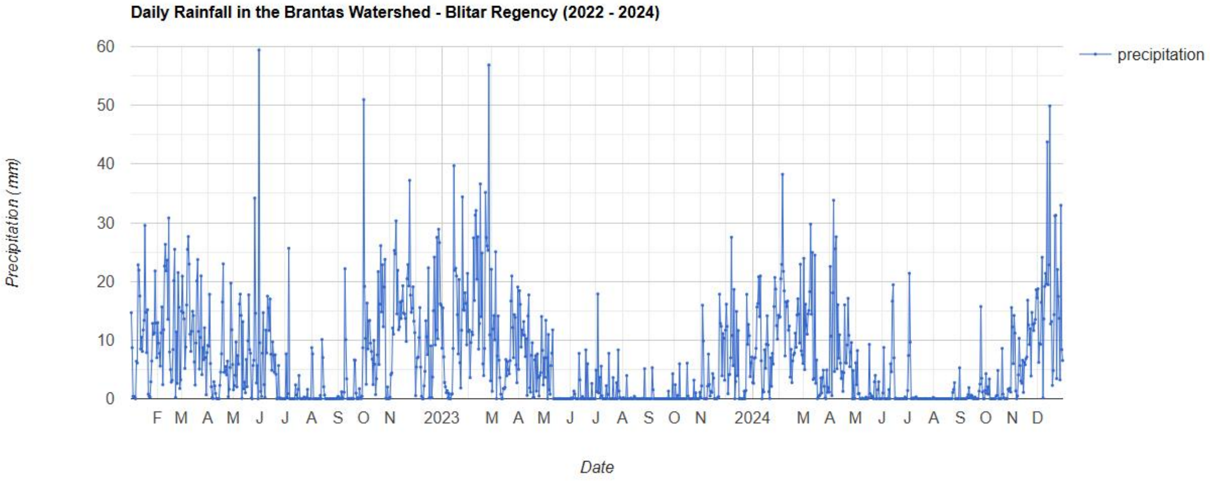

Fig 4. Rainfall Data with Time Series 2022-2024

Table 2. Recapitulation of Climate Data for Blitar Regency

No.	Year	Climate Parameters		Temperature (°C)	Humidity (%)	Exposure time (hours)	Wind Speed (km/h)
1	2022	Month	Jan	24,2	81,8	3,9	5,3
2			Feb	23,9	83,2	4,3	6,0
3			Mar	24,3	83,1	4,4	5,8
4			Apr	24,3	78,8	6,2	5,2
5			May	24,8	77,9	6,7	6,3
6			Jun	23,6	80,5	6,2	5,9

No.	Year	Climate Parameters		Temperature (°C)	Humidity (%)	Exposure time (hours)	Wind Speed (km/h)
7			Jul	23,3	75,6	7,3	7,0
8			Ags	23,5	76,6	7,0	7,9
9			Sep	24,1	78,7	6,8	7,8
10			Okt	23,7	84,8	4,2	6,4
11			Nov	24,0	85,1	3,9	4,7
12			Des	24,5	79,3	4,9	7,3
13	2023	Month	Jan	24,3	80,3	5,1	6,9
14			Feb	23,8	84,0	2,8	6,4
15			Mar	24,1	80,1	5,8	6,1
16			Apr	24,1	82,7	4,7	5,8
17			May	24,4	74,1	6,8	6,9
18			Jun	23,9	78,4	6,8	6,4
19			Jul	22,6	77,9	6,8	7,4
20			Ags	22,8	73,0	8,4	7,7
21			Sep	23,7	68,0	8,3	8,2
22			Okt	26,1	65,7	9,1	9,3
23			Nov	26,5	73,1	6,5	6,7
24			Des	26,0	75,9	6,3	6,2
25	2024	Month	Jan	25,7	80,2	4,9	6,2
26			Feb	25,6	81,7	4,7	4,6
27			Mar	26,0	79,4	4,6	5,6
28			Apr	26,4	79,0	5,8	6,4
29			May	26,4	72,1	7,5	7,0
30			Jun	25,6	73,8	6,6	6,1
31			Jul	23,4	72,9	7,2	7,1
32			Ags	23,3	73,1	7,2	7,7
33			Sep	24,6	72,2	6,9	7,4
34			Okt	25,6	72,0	7,1	8,1
35			Nov	25,8	77,9	5,6	6,8
36			Des	24,4	87,0	3,1	5,0

The second stage is the calculation of Potential Evapotranspiration (ETo), as pointed out in (1), using the Modified Penman Method, in accordance with the KP-01 reference [11]. This calculation uses climatological data obtained from BMKG, covering parameters such as temperature, relative humidity, duration of sunshine, and wind speed. The calculation begins with determining the values of $\varepsilon\gamma$, w, and f(t) based on air temperature, followed by the calculation of εd and f(εd). Radiation components, including shortwave radiation (Ry), R_s, R_{ns}, and R_{n1}, are calculated by considering the sunshine brightness factor and wind speed. The Rn value is obtained from the difference between R_{ns} and R_{n1}. Finally, all these components are combined to obtain the monthly ETo value.

Table 3. Recapitulation of Evapotranspiration Data in Blitar Regency Using the Penman Monteith Method

Year	Evapotranspiration (mm/hr) Blitar Regency Using the Penman Monteith Method												Total
	Jan	Feb	Mar	Apr	Mei	Jun	Jul	Ags	Sep	Okt	Nop	Des	
2022	6,76	6,99	6,74	6,22	6,67	5,72	7,12	8,28	9,29	6,73	6,08	8,46	85,06
2023	8,21	6,22	7,96	5,40	7,37	6,34	6,71	9,31	12,10	14,68	10,38	9,43	104,11
2024	8,01	7,07	7,46	6,68	8,21	6,95	7,50	8,95	10,41	11,44	9,08	5,53	97,29
Average	7,66	6,76	7,39	6,10	7,41	6,34	7,11	8,85	10,60	10,95	8,51	7,81	

The third stage is the monthly discharge simulation using the F.J. Mock Method, with calculations based on the water balance principle. This stage uses monthly rainfall data (P) processed from the CHIRPS satellite and Potential Evapotranspiration (ETo) data from the Modified Penman Method calculations as primary inputs. Based on the data used, several initial parameters and coefficients were set for this model: a Watershed Area of 1588.79 km^2, a Maximum Soil Moisture Capacity (MaxSMC) of 200 mm, and an initial groundwater storage volume (V_{n-1}) at the start of the simulation of 200 mm. Furthermore, values were also set for the open land surface coefficient (m) at 30%, the infiltration coefficient (i) at 0.30, and the groundwater flow recession factor (k) at 0.50.

The calculation process begins by estimating the actual evapotranspiration (E_t) value. Subsequently, the amount of water reaching the ground surface (A_s) is calculated by subtracting E_t from rainfall (P). This A_s value is then allocated to fill the soil storage (SS) up to its maximum capacity, with the remaining water becoming water surplus (WS). The WS value is then divided into two components: infiltration (I), which is calculated by multiplying it by the infiltration coefficient (i), and the remainder becoming direct runoff (DR). The infiltration component (I) is used to update the groundwater storage volume (V_n) and calculate the change in groundwater volume (DV_n). From this, the base flow (BF) is calculated as the difference between infiltration (I) and the change in groundwater volume (DV_n). Finally, the total runoff (T_{ro}) is obtained by summing the direct runoff (DR) and the base flow (BF). This total runoff value is converted into monthly modelled discharge (Q_{model}) in units of m^3/second using the watershed area and the appropriate time conversion factor.

Table 4. Monthly Discharge Model F.J. Mock Method

Year	**Monthly Discharge Data Using the F.J. Mock Method in Blitar Regency (m^3/sec)**												**Total**
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Ags**	**Sep**	**Okt**	**Nov**	**Des**	
2022	39,34	79,40	61,53	28,04	19,00	13,74	9,31	6,52	4,71	3,19	9,67	3,14	277,59
2023	3,61	105,47	22,01	15,92	10,78	7,80	5,28	3,70	2,68	1,81	1,31	0,89	181,26
2024	0,04	3,09	0,65	0,47	0,32	0,23	0,16	0,11	0,08	0,05	0,04	0,12	5,37
Average	14	63	28	15	10	7	5	3	2	2	4	1	

The final stage in this research is the dependable flow analysis. This analysis is conducted on a monthly scale using the discharge data simulated by the F.J. Mock Method. Dependable flow is defined as a specific discharge magnitude associated with a specific probability, used as a basis for water resource planning, such as for irrigation, raw water supply, and Hydroelectric Power Plant (PLTA) needs. The analysis procedure begins by sorting the modelled discharge data from the largest value to the smallest. After sorting, the probability of exceedance for each discharge value is calculated using the Weibull equation formula (SNI 6738:2015). In this formula, m is the rank of the data, and n is the total number of data points. This approach allows for the determination of discharge at a certain reliability level (e.g., Q70, Q80, or Q90). The results of this calculation are then used to create a Flow Duration Curve, which serves as the basis for effective planning of raw water supply, irrigation, and energy.

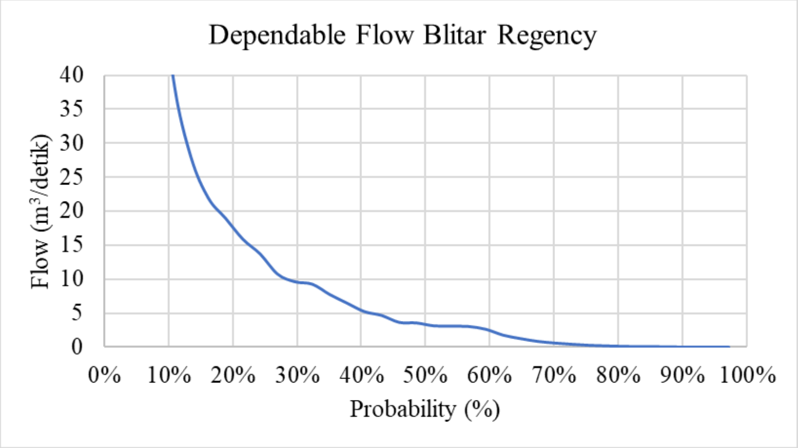

Fig 5. Rating Curve

4. Conclusion

Based on the calculation results and the application of the Google Earth Engine (GEE) platform, it serves as an effective and efficient tool for estimating dependable flow in the Brantas River Basin. By utilizing daily runoff data from the ERA5-Land global climate model, time-series analysis for the 2021–2024 period can be conducted quickly, unconstrained by the limitations often encountered with field observation data. The main findings indicate that GEE is capable of consistently processing large-scale runoff data to construct a Flow Duration Curve (FDC). From this FDC, the research successfully extracted estimated dependable flow values (such as $Q_{70} = 0.65$ m^3/s, $Q_{80} = 0.19$ m^3/s, and $Q_{90} = 0.07$ m^3/s) for the Brantas River Watershed.

These results affirm that the estimation method based on GEE and ERA5-Land data has great potential as an alternative and a complement to conventional observation data (AWLR). This approach offers a solution to overcome the problems of missing data and uneven station distribution, thereby supporting water resource planning and management in the Brantas River Basin that is more adaptive, evidence-based, and technology-based. For future research, it is recommended to validate these dependable flow estimation results from ERA5-Land against field observation discharge data (if available) to determine the level of accuracy and any correction factors that may be necessary.

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