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Genetic Algorithm-Based NRECA Parameter Calibration for Rainfall-Discharge Modeling in Rejoso Watershed

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Abstract: The Rejoso watershed in Pasuruan Regency is a critical water resource that supports various sectors, including agriculture and domestic needs. However, the imbalance between water demand and availability, exacerbated by insufficient discharge measurement infrastructure, necessitates alternative approaches to determine river discharge. This study utilizes the NRECA method combined with Genetic Algorithms (GA) to estimate river discharge by calibrating key hydrological parameters, Percent Sub-Surface (PSUB) and Ground Water Flow (GWF). Data from seven rainfall stations and AWLR Winongan were analyzed for the 2004-2023 period. Calibration of the NRECA model was carried out using the Nash-Sutcliffe Efficiency (NSE) and correlation coefficient (R), both achieving values close to 1, indicating an excellent model fit. The study highlights the applicability of GA for optimizing hydrological parameters and demonstrates the potential of the NRECA-GA method in improving discharge predictions in watersheds with limited data. These findings contribute to more effective and sustainable water resource management in the Rejoso watershed.

Keywords: Calibration; Discharge; Genetic algorithm (GA); GWF; PSUB; Rainfall

Introduction

The availability of complete and accurate discharge data is essential for the sustainable utilisation of water resources (Asdak, 2020). Inadequate discharge data can lead to inaccuracies in planning and managing the water resources of a watershed, including the Rejoso watershed in Pasuruan Regency (Nisa et al., 2024). This watershed has a strategic role as the main provider of clean water for Pasuruan and surrounding areas, supporting vital sectors such as agriculture and fisheries, as well as meeting the needs of local communities (Amalia et al., 2023). With significant water resource potential, the Rejoso watershed plays an important role in maintaining ecosystem sustainability and the local economy (Putri et al., 2023).

However, balanced watershed management faces increasingly complex challenges. Management imbalances can be caused by various factors, such as increasing water demand due to population growth, uncontrolled land use change, environmental degradation, pollution, inadequate water management infrastructure, and ineffective management policies (Kurniawan et al., 2019). These conditions contribute to reduced water availability in some parts of the watershed and pose a risk to the sustainability of water resources management in the region (Supiyati et al., 2024).

These problems are exacerbated by limited discharge measurement infrastructure such as AWLRs, which often have limitations in data length, accuracy and equipment reliability (Hadihardaja et al., 2010). As a result, the ability to predict river discharge is limited,

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which can impact decision-making related to water resources management (Fathoni et al., 2016).

In this context, the conversion of rainfall data (Ardana et al., 2025) into discharge through modelling is a potential solution to overcome the limitations of existing discharge data (Putri et al., 2023). This research uses the NRECA method, which is recognised in the Irrigation Network Planning Criteria (KP-01) as one of the reliable discharge modelling standards (KP-01, 2013). What distinguishes this research from previous studies is the application of Genetic Algorithm to determine key watershed parameters, namely Percent Sub-Surface (PSUB) and Ground Water Flow (GWF) (Hawari et al., 2025). Genetic Algorithm has advantages in solving complex optimisation problems, so it can produce more accurate and efficient solutions (Syaakiroh et al., 2024).

This research is important because it provides a new approach in modelling discharge using a combination of the NRECA method and Genetic Algorithm, which has not been widely applied to the Rejoso watershed (Nurviana et al., 2023). Thus, this research is expected to make a significant contribution in improving the accuracy of discharge prediction (Gejadze et al., 2022), supporting sustainable water resources management, and providing practical solutions to overcome the challenges of limited discharge data in the watershed (Anindya et al., 2022).

Method

This research is located in the Rejoso watershed, Pasuruan Regency which has an area of 285.355 km2 with 7 rainfall stations and AWLR Winongan used for analysis.

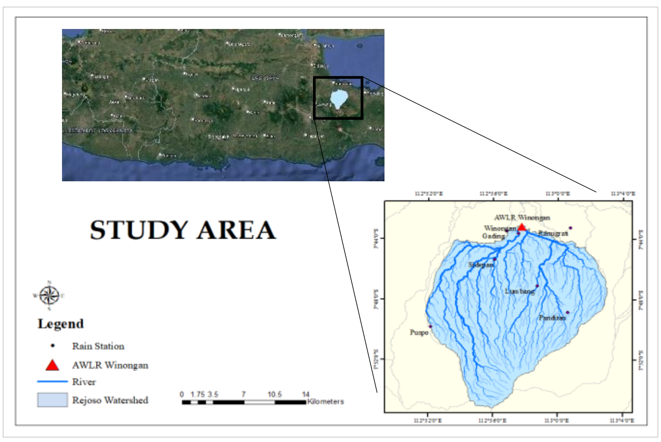

Figure 1. Rejoso Watershed

In this research, a structured approach was essential to facilitate the research process. The first step involved collecting data from various relevant agencies required for the study (Alnino et al., 2022). Next, standard procedures in hydrological data processing were carried out, starting with:

Data Quality Test

Data Consistency Test (Rainfall – Double Mass Curve Analysis, dan Discharge – Rescaled Adjusted Partial Sums atau (RAPS)), Trend Absence Test (Spearman Test, Mann-Whitney Test, and Tanda Cox & Stuart Test), Persistence Test dan Stationary Test (F-test dan T-test).

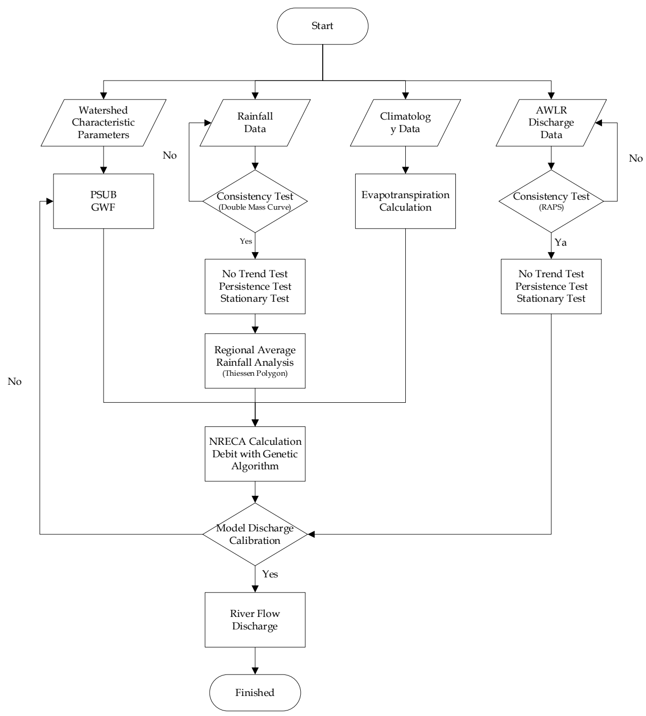

Figure 2. Research flow chart

Regional Average Rainfall

Calculating regional average rainfall using the Polygon Thiessen Method, due to the uneven distribution of rainfall stations. This method helps determine the relative influence of each rainfall station on the Rejoso watershed.

Potential Evapotranspiration (PET)

Potential Evapotranspiration is derived from climatological data (Jayanti et al., 2023), including temperature, relative humidity, sunshine duration, and wind speed. Potential Evapotranspiration was calculated using the Modified Penman and Penman-Monteith Methods that have been modified to FAO standards, with the help of Cropwat 8.0 software. Then, the results of both methods will be compared with Pan Evaporation (field data), and the calculation results that have a better correlation will be used in the calculation.

NRECA Method

The National Rural Electric Cooperative Association (NRECA) model is a simplified approach used to estimate surface runoff based on monthly water balance. The mathematical relationship within this model follows a sequence of equations as described below.

The average streamflow discharge (Q) is calculated as the sum of direct flow (DF) and groundwater flow (GWF):

$$Q = DF + GWF \tag{1}$$

Direct flow (DFDFDF) is determined by the difference between excess moisture (EM) and groundwater storage (GWS):

$$DF = EM - GWS \tag{2}$$

Groundwater flow (GWF) is obtained by multiplying the groundwater storage (GWS) by parameter P2:

$$GWF = P2 \times GWS \tag{3}$$

Groundwater storage (GWS) is defined as a fraction of excess moisture, calculated by multiplying P1 by EM:

$$GWS = P1 \times EM \tag{4}$$

Excess moisture (EM) is derived from the product of the excess moisture ratio (EMR) and water balance (WB):

$$EM = EMR \times WB \tag{5}$$

The water balance (WBWBWB) is calculated as the difference between monthly rainfall (Rb) and actual evapotranspiration (AET):

$$WB = Rb - AET \tag{6}$$

Actual evapotranspiration (AET) is computed from the ratio of actual to potential evapotranspiration (PET):

$$AET = (AET / PET) \times PET \tag{7}$$

Soil moisture content (Wi) is calculated by dividing the initial soil moisture storage (Wo) by a nominal factor (N):

$$Wi = Wo / N \tag{8}$$

The nominal factor (N) itself is determined based on the annual rainfall (Ra):

$$N = 100 + 0.20 \times Ra \tag{9}$$

Parameters P1 and P2 represent the hydrological characteristics of the soil. Parameter P1 reflects the soil's infiltration capacity into the shallow layer, while P2 indicates the release rate of water from the subsurface storage into the baseflow.

In this study, P1 and P2 are referred to as PSUB and GWF, respectively. PSUB represents the proportion of excess moisture stored in the subsurface as groundwater storage, whereas GWF represents the proportion of groundwater storage released into the stream as baseflow. The PSUB and GWF columns in the calculation table refer to the parameter values used in stream flow simulation (Widyaningsih et al., 2021).

The calibration of PSUB and GWF parameters was conducted using a genetic algorithm approach through Microsoft Excel Solver. The goal of calibration (Ndiritu et al., 2001) was to obtain the optimal combination of parameter values that best match the simulated discharge with observed streamflow data (AWLR) (Wu et al., 2015). This process was performed iteratively by minimizing the difference between simulated and observed discharge (Joubier et al., 2025), both quantitatively using statistical indicators such as the NSE and R, and qualitatively through visual inspection of hydrograph patterns.

By employing calibrated PSUB and GWF parameters, the NRECA model can represent the transformation of rainfall (Wu et al., 2015) into runoff with sufficient accuracy, particularly in watersheds with limited hydrological data availability.

Determination of Percent Sub-Surface (PSUB) and Ground Water Flow (GWF) Parameters using Genetic Algorithm with Microsoft Excel Solver Add-Ins for Calibration

The Percent Sub-Surface (PSUB) and Ground Water Flow (GWF) parameters are essential components in discharge modeling using the NRECA method (Masruroh et al., 2022). PSUB reflects the percentage of soil moisture that flows as direct surface flow or becomes groundwater recharge. A high PSUB value indicates low soil infiltration, so that most of the rainwater (Hasanah et al., 2013) goes directly into surface flow, while a low PSUB value reflects a soil condition with high infiltration, where most of the rainwater soaks into the soil. Based on KP-01 guidelines (Ministry of Public Works, 2013), PSUB values used in modeling are usually in the range of 0.3 to 0.9, depending on soil characteristics, land cover, and hydrological conditions of the watershed.

Meanwhile, GWF describes the percentage of groundwater stored in groundwater reserves that flows into the river as baseflow. A high GWF value indicates a significant contribution of baseflow to stream discharge (Kumar et al., 2024), which often occurs in watersheds with porous geological structures and good groundwater recharge areas. Conversely, a low GWF value indicates the dominance of surface flow in river discharge (Gashi et al., 2011). Based on the research of Hadihardaja et al. (2010) and Fathoni et al. (2016), GWF values are generally in the range of 0.01 to 0.9, depending on the geological structure, topographic conditions, and groundwater flow patterns in a watershed.

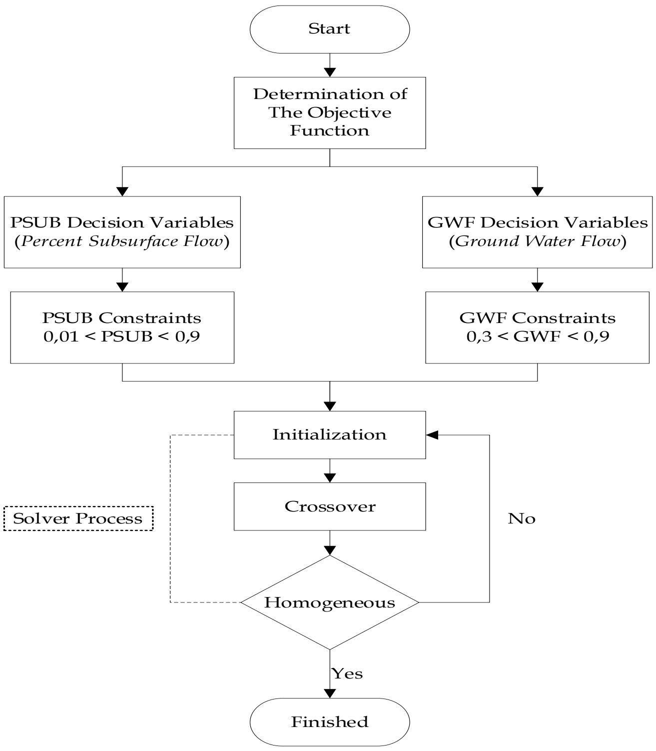

Figure 3. Genetic algorithm process NRECA method

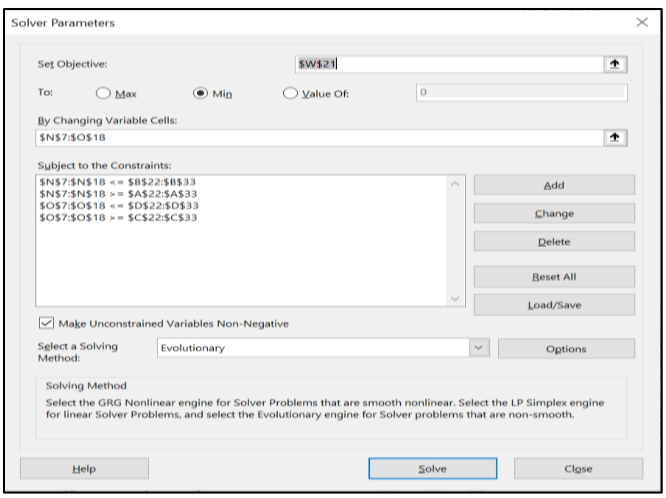

Figure 4. Constraint variables in the solver

Objective Function

The objective function in this calculation is defined as the minimization of the sum of the squared differences ∑(model discharge - AWLR discharge)². This stage aims to achieve the best fit between the model discharge and the observed discharge by minimizing the value of the objective function.

Decision Variable

In the NRECA calculation, the decision variables are the PSUB and GWF coefficients (Alnino et al., 2022). These variables are adjusted iteratively until the model's performance evaluation metric, such as the Nash-Sutcliffe Efficiency (NSE), approaches an ideal value of 1, indicating high agreement between modeled and observed discharges.

Constrains

This section defines the constraints or allowable ranges for the PSUB and GWF values. The applied ranges are 0.3 < PSUB < 0.9 and 0.01 < GWF < 0.9. These constraints ensure that the optimization remains within realistic bounds for hydrological parameters.

Solver Method

The solver method chosen for this optimization is the Evolutionary Solver. This method is selected because it consistently produces optimal results in complex optimization scenarios compared to other solver methods.

Perform Calibration

Nash-Sutchliffe Efficiency (NSE)

This test aims to ensure the accuracy of the correlation between the measured data and the calculated data. The equation used is:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Pi - Qi)^2}{\sum_{i=1}^{N}(Pi - \bar{P}i)^2} \quad (10)$$

Decription:
NSE = Nash-Sutchliffe coeficient
P_i = Field observation value (m³/dt)
Q_i = Modeling result value (m³/dt)
$\bar{P}_i$ = Average value of field observation (m³/dt)
N = Number of data

Table 1. Classification of NSE Value

Value Range	Performance Rating
0.75 < NSE ≤ 1.00	Very Good
0.65 < NSE ≤ 0.75	Good
0.50 < NSE ≤ 0.65	Meets
NSE ≤ 0.50	Does Not Meet

Correlation Coefficient (R)

This test is used to determine whether the linear correlation between the two variables is strong or not. The equation used is:

$$R = \frac{N\sum_{i=1}^{N} PiQi - \sum_{i=1}^{N} Pi \, x \sum_{i=1}^{N} Qi}{\sqrt{\sum_{i=1}^{N} Pi^2 - \left(\sum_{i=1}^{N} Pi\right)^2} \sqrt{\sum_{i=1}^{N} Qi^2 - \left(\sum_{i=1}^{N} Qi\right)^2}} \quad (11)$$

Description:
R = Correlation coefficient
P_i = Field observation value (m^3/dt)
Q_i = Modeling result value(m^3/dt)

After obtaining the R value, the value will be classified based on the level of relationship, the following is a clasification table of criteria from the value of the correlation coefficient:

Table 2. Classification of Correlation Coefficient (R) Value (Sugiyono, 2019)

Value Range	Level of Relationship Linkage
0.00 – 0.19	Very Low
0.20 – 0.39	Low
0.40 – 0.59	Medium
0.60 – 0.79	Strong
0.80 – 1.00	Very Strong

Result and Discussion

Data Quality Test

This study uses rainfall data and discharge data for 20 years (2004-2023). Rainfall data comes from 7 rain posts located in the research location, namely the Lumbang, Panditan, Puspo, Ranu Grati, Sidepan, Winongan, and Gading rain posts. From this data, data quality testing is then carried out. Based on the results of the calculation of the quality test, the discharge data is consistent (Jukić et al., 2015), while in the rain data there is some inconsistent data, but after multiplying with the correction factor then the data is consistent. In the absence of trend test there is no data that has a trend and for the stationary test and persistence test all data is accepted.

Regional Average Rainfall

In analyzing the regional average rainfall using the thiessen polygon method, so that the area value of each rain post and the thiessen coefficient (Kr) of each rain post are obtained.

Table 3. Area and Thiessen Coefficient (Kr)

Rain Station	Area (km^2)	Kr
Lumbang	55.55	0.19
Panditan	69.30	0.24
Puspo	80.40	0.28
Ranu Grati	13.99	0.05
Sidepan	51.25	0.18
Winongan	12.91	0.05
Gading	1.97	0.01
Amount	285.36	1.00

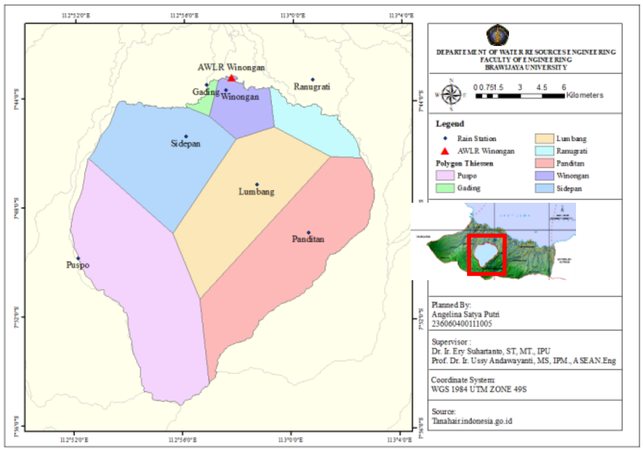

Figure 5. Thiessen polygon map rejoso watershed

Potential Evapotranspiration (PET)

Evapotranspiration calculations were carried out using two methods, namely Penman Modification and Penman Monteith with Cropwat 8.0 software.

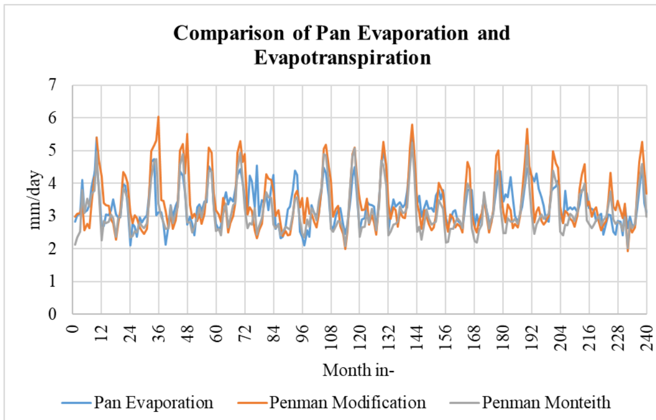

Figure 6. Comparison of pan evaporation and evapotranspiration

Based on Figure 4, the calculation of evapotranspiration in 2004-2023, it can be seen that the Penman Monteith method is more following the pattern (trend). And when compared with Pan Evaporation (data in the field) with the results of the correlation coefficient test on the Penman Modification method is 0.753 while for Penman Monteith is 0.842. So in the next calculation, the evapotranspiration value used is the value of the Penman Monteith method.

NRECA Model Calibration Process with Genetic Algorithm

In the NRECA method discharge calculation, the parameters determined by the Genetic Algorithm in the Microsoft Excel solver feature are the PSUB and GWF parameters (Azadgar et al., 2025). PSUB and GWF parameters are determined by the Genetic Algorithm (Cheng et al., 2002) in each month, so that these parameters have different values each month.

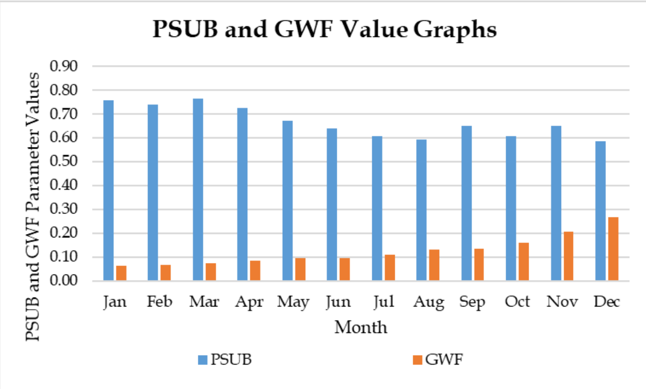

Figure 7. Bar Chart of GA Values of PSUB and GWF Parameters

NRECA Discharge

Calculation of the NRECA method in this study to determine the value of PSUB and GWF parameters using Genetic Algorithms in each month with the help of a solver found in Microsoft Excel. So as to produce different PSUB and GWF values each month. The following is a recapitulation of the calculation results of the NRECA method:

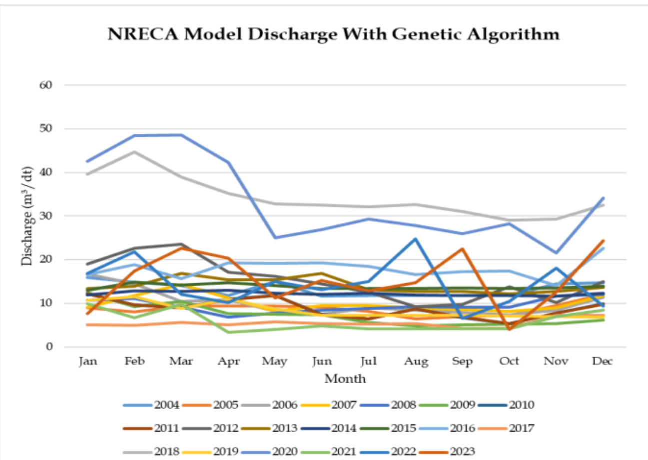

Figure 8. NRECA model discharge with genetic algorithm

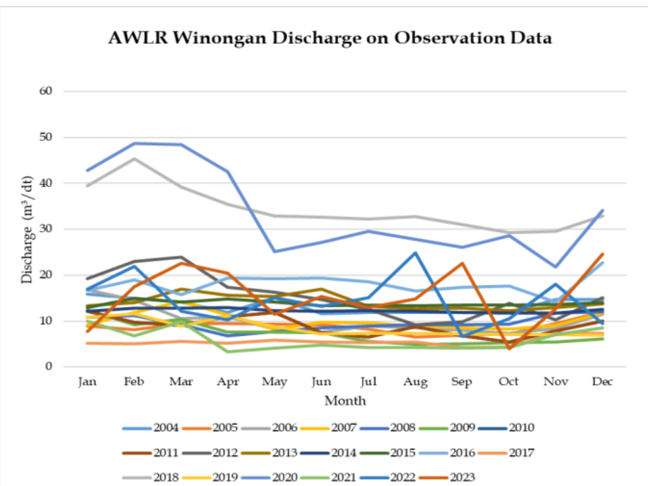

Figure 9. AWLR Discharge on obsevation data

Calibration Process

Calibration testing is carried out using two methods, namely the Nash-Sutcliffe Efficiency (NSE) Test and the Correlation Coefficient (R) Test (Nasseri et al., 2008). The NSE test measures the model's accuracy in replicating observed discharge data, with values closer to 1 indicating excellent performance. The Correlation Coefficient (R) Test evaluates the strength of the linear relationship between observed and simulated values, with higher values reflecting strong agreement. These complementary tests ensure a thorough evaluation of model performance. A summary of the calibration results is presented in the following table.

Table 4. Recapitulation of 20 Years Calibration Results

Year	NSE		Correlation (R)	
	Value	Interp.	Value	Interp.
2004	1.00	VG	1.00	VG
2005	1.00	VG	1.00	VG
2006	1.00	VG	1.00	VG
2007	1.00	VG	1.00	VG
2008	1.00	VG	1.00	VG
2009	1.00	VG	1.00	VG
2010	1.00	VG	1.00	VG
2011	1.00	VG	1.00	VG
2012	1.00	VG	1.00	VG
2013	1.00	VG	1.00	VG
2014	0.95	VG	0.99	VG
2015	0.99	VG	1.00	VG
2016	1.00	VG	1.00	VG
2017	1.00	VG	1.00	VG
2018	1.00	VG	1.00	VG
2019	1.00	VG	1.00	VG
2020	1.00	VG	1.00	VG
2021	1.00	VG	1.00	VG
2022	1.00	VG	1.00	VG
2023	1.00	VG	1.00	VG

Based on Table 4, all years get calibration results with "Very Good" interpretation. It can be seen that the best calibration results are in 2022 with an NSE value of 0.99976 and a correlation value of 0.99997. This is because it has the highest Nash-Sutcliffe Efficiency and Correlation Coefficient values among all methods.

This study determines the PSUB and GWF parameters on a monthly basis using a Genetic Algorithm to capture the influence of seasonal variations, such as changes in soil moisture and water saturation (Nour et al., 2021), on the hydrological response of the watershed. Although these watershed characteristics are generally considered stable within a year, this approach was taken to accommodate significant seasonal dynamics. To avoid the risk of overfitting, the calibration process is complemented by cross-validation using different data (Jian et al., 2021), so that the model remains reliable in predicting discharge beyond the calibration data.

Conclusion

All the results of the calibration test between the NRECA model discharge and the observed discharge showed Very Good throughout the 20 years. Where the calibration results of the NSE method are almost close to the value of 1 which is interpreted as "Very Good" as well as for the R method which is interpreted as "Very Good". The calibration results show very high NSE values and correlation coefficients, indicating a very good match between the modelled discharge and the observed data. Nonetheless, these results have been thoroughly reviewed to ensure that no overfitting or errors occurred in the process of model implementation and optimisation algorithms. To minimise the risk of bias, the discharge data has been strictly divided into two groups, 70% for calibration and 30% for validation, ensuring no overlap between the two data sets. The optimisation process utilised PSUB and GWF parameters, which were selected based on their physical relevance to the hydrological characteristics of the watershed. The number of optimised parameters was limited to avoid the risk of overfitting that often occurs in models with a limited amount of data. In addition, cross-validation was performed to ensure the ability of the model to predict data not included in the calibration set. It should be realised that field data often contain uncertainties due to temporal and spatial variations in measurements. Therefore, while high NSE and correlation values reflect strong relationships in the data, additional validation with independent data from different periods or locations will be conducted to test the generalisability of the model (Maulidya et al., 2025). This step aims to ensure that the model not only fits the calibration data, but also has good predictive ability in a broader scenario.

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All authors contributed to writing this article.

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Conflicts of Interest
The authors declare no conflict of interest.

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