Sensitivity Analysis of Calibration in the Water Evaluation and Planning (WEAP) Model for Water Resource Management in Keyang, Slahung, Sungkur Watershed

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Abstract

Water availability is a critical issue as population growth increases, while water resources remain limited and insufficient to meet rising demand. This is evident in the Keyang, Slahung, and Sungkur sub-watersheds in Ponorogo Regency, East Java, which suffer from drought during the dry season and flooding in the rainy season. To support sustainable water resource management, accurate modelling tools are needed to reflect real field conditions. The Water Evaluation and Planning (WEAP) model is commonly used to simulate integrated water resource management, and model calibration is essential to ensure its reliability. This study employed the soil moisture method, which requires data on water availability from both surface water and groundwater, as well as water demand data across domestic, non-domestic, irrigation, and livestock sectors. Model calibration resulted in optimum parameter values: Z1 = 0, Z2 = 0, DWC = 1000, DC = 250, RRF = 10, RZC = 300, SWC = 1000, and PFD = 0.05. Based on these values, the model achieved a Nash-Sutcliffe Efficiency (NSE) of 0.85 (good category), RMSE of 5.35 (good enough), PBIAS of 19.99 (good enough), R^2 of 0.84 (medium influence), and MAPE of 0.42 (very accurate). These results confirm that the model reliably represents actual hydrological conditions in the study area.

Keywords

Calibration, Ponorogo, sensitivity analysis, water resource management, WEAP

INTRODUCTION

Watersheds are areas that include tributaries that collect and flow water to the sea [1]. Ponorogo Regency has three sub-watersheds, namely Keyang (328.8 km^2), Slahung (544.8 km^2), and Sungkur (314.8 km^2). Based on data from the Central Statistics Agency (BPS), the population of Ponorogo will increase from 964,253 in 2022 to 972,582 in 2023, with a growth rate of 0.86%. Population growth leads to increased water demand, which risks exacerbating the exploitation of water resources. The Ponorogo watershed is in a critical category due to forest land conversion that does not respect conservation principles. In addition, the area is prone to drought in the dry season and flooding in the rainy season, which impacts several subdistricts such as Slahung, Mlarak, Sawo, Balong, Badegan, and Jambon.

Based on the above explanation, the problem that occurs requires a solution. Changes in hydrology and elements that affect water resources can be a solution to overcome this problem. Evaluating water resources is not easy and requires many elements to be considered for calculation [2]. Knowledge of spatial and temporal distribution is also important. The most optimal alternative solution is to develop a hydrological model to analyse water availability using the WEAP (Water Evaluation and Planning) system. WEAP is an application used for water balance modelling, which links hydrological inputs in the form of water availability at various locations [3]. WEAP can also divide water management for various sectors [4]. This application also offers scenario analysis in an approach that is easy to understand and provides various model results in an easy-to-understand way [5]. There are several methods in WEAP for modelling basin processes, such as rainfall runoff method (simplified coefficient and soil moisture), irrigation demands only method, and plant growth methods [6]. The rainfall-runoff (soil moisture) method was used to calculate surface flow with climate data as input.

To obtain accurate model results that are close to the observation data, this process requires calibration using WEAP. The calibration involves several parameters that require a trial and error process to ensure a match between the model and real conditions in the field.

This study on parameter sensitivity analysis presents novelties compared to prior research. The novelty lies in the determination of calibration parameter values for the WEAP model that are specific to the local hydrological conditions of the Keyang, Slahung, and Sungkur sub-watersheds, which have not been previously investigated. Utilizing a sensitivity analysis approach, this research identifies the key parameters that most significantly influence model performance. The parameter values obtained through the calibration process are not only adjusted to observed river discharge data but also reflect the physiographic characteristics and land use patterns. Therefore, these calibrated parameter values constitute a novel contribution that can serve as an initial reference for the development of water resource models in regions exhibiting spatial complexity, such as the study area.

RESEARCH SIGNIFICANCE

This research is important to improve the accuracy of water availability modelling using WEAP (Water Evaluation and Planning), with a focus on calibrating the model to reflect real conditions in the field. Proper calibration with the soil moisture method will improve the reliability of the model and optimize water management in critical watersheds. An overview of the approach to the method used can be seen on Figure 1.

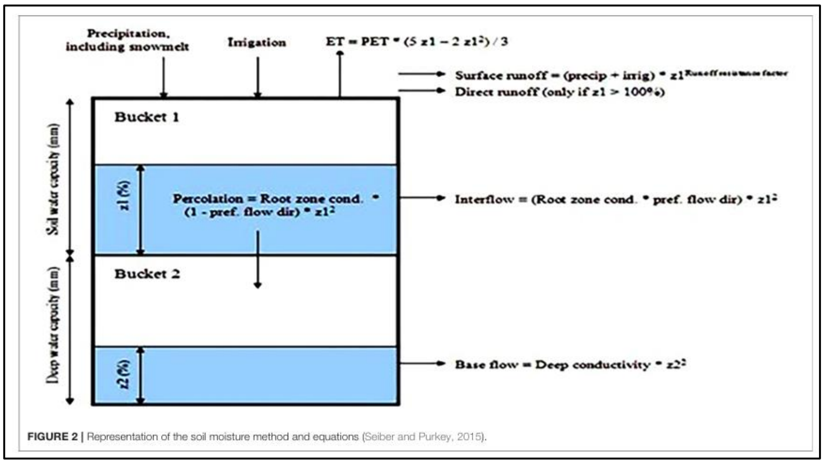

FIGURE 2 | Representation of the soil moisture method and equations (Seiber and Purkey, 2015).

Figure 1 Soil Moisture Method
Source: Opere et al., 2022

METHODOLOGY

The method used is soil moisture. This method enables the characterization of the impacts of land use, climate, and/or soil type on these processes. It involves a one-dimensional, two-layer ("bucket") soil moisture dynamic system that utilizes empirical functions to partition water into evapotranspiration (ET), surface runoff, subsurface runoff, and deep percolation for a subbasin unit at the root zone [7].

The analysis using this method requires data on water availability from both rivers and groundwater. It also necessitates an assessment of water demand from domestic, non-domestic, irrigation, and livestock sectors. Subsequently, model simulation is conducted. During the simulation process, a parameter sensitivity analysis is performed in accordance with the characteristics of the study location. Parameter values are varied to ensure that the simulation results correspond with field observations.

A. COLLECTION OF TECHNIQUE DATA

The required data is secondary data. The Keyang, Slahung, and Sungkur sub-watershed maps can be obtained through the website: tanahair.Indonesia.go.id. Rainfall data from 2014-2015 and the global cropping plan (RTTG) come from the Ponorogo DPUPKP. The map of the homeland basin (CAT) comes from the Office of Energy and Mineral Resources. Climatological data and AWLR Sekayu observation discharge from 2014-2015 come from the Bengawan Solo River Basin Office. Data on the number of livestock, public facilities, and population from 2014-2015 come from the Ponorogo Regency Statistics Agency.

B. TECHNIQUE ANALYSIS

Analysis supply water uses F.J. Mock method. With this method, the magnitude of the surface flow can be calculated using rainfall data, hydrological characteristics of the catchment area, and evapotranspiration. This method involves calculating rainfall, calculating potential evapotranspiration, and limited evapotranspiration [8].

After analysing the supply water, the next step is to analyse the water demand. Water demand comes from domestic, non-domestic, livestock, and irrigation aspects.

The calculation of domestic water demands is as follows:

Domestic water demand = Population x water requirement coefficient

The calculation of non-domestic water demand is 20% of domestic water demand.

The calculation of average water demand for livestock depends on the population/number of livestock and the type of livestock [9]. The calculation of livestock water demand is as follows:

Livestock water demand = Population x water requirement coefficient

Meanwhile, irrigation water demand is obtained from the global cropping pattern plan (RTTG) because irrigation is used to meet the needs of rice fields only [10]. The calculation of irrigation water demands is as follows:

$$\mathrm{IR} = \frac{NFR}{e}$$

Notes:
IR: Irrigation water requirement
e : Irrigation efficiency

After preparing the data, the next step is modelling in WEAP application. The map of the research location is imported into WEAP along with the river network. Then digitize the river, supply, catchment, and non-irrigation and irrigation demand. These symbols are connected by transmission links and return flows. Input landuse area on catchment symbol. Then input all data including discharge observations.

In the schematic view there are several symbols. The red circle symbol shows the demand site. Demand sites can represent irrigated or non-irrigated areas. The green square symbol indicates groundwater. The blue line symbolises a river. The red circle symbol represents the catchment. While the green line is the link from the supply water to the irrigated area (demand site). The red line is the return flow from the demand site to the river. Schematic view can be seen in Figure 2.

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n})(Qsi - Qmi)^2}{\sum_{i=1}^{n})(Qsi - Qm)^2}$$

Notes:
Qsi: Simulation discharge
Qm: Observation discharge
Qmi: Observation average discharge

Root Mean Square Error (RMSE) is a form of test used to measure the accuracy of the data used in research. RMSE is used to obtain the difference between the simulated value of the model and the actual observed value. The RMSE value displays the error rate of simulation results and observations. If the RMSE value is close to zero (0), the smaller the error rate in the modelling [11].

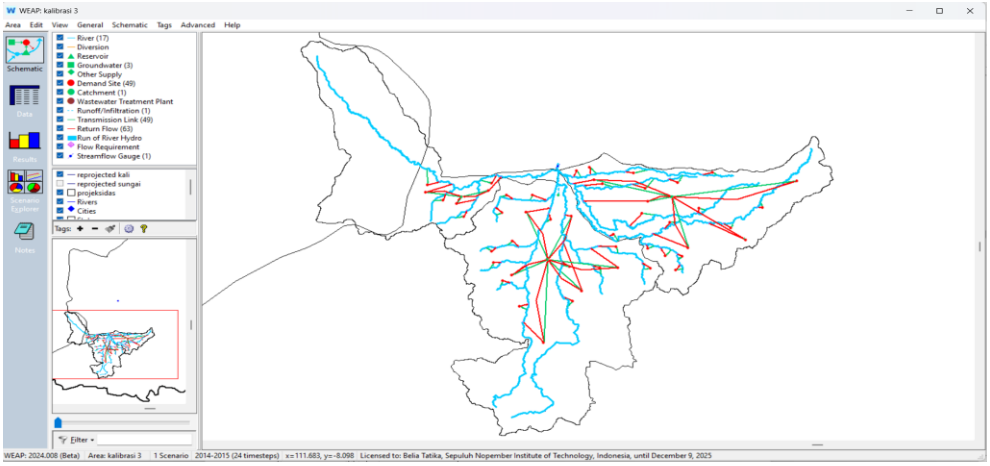

Figure 2 Schematic View on WEAP

In performing the error and trial process, there are several parameters that need to be changed which can be seen in Table 1. Table 1 shows default values and those values can be changed for sensitivity analysis of calibration.

Table 1. The Parameter Values

Parameter	Default Value
Z1 [%]	30
Z2 [%]	30
DWC (Deep Water Capacity) [mm]	1000
DC (Deep Conductivity) [mm/month]	20
RRF (Resistance Runoff Factor) [No Unit]	2
RZC (Root Zone Conductivity) [mm/month]	20
SWC (Soil Water Capacity) [mm]	1000
PFD (Preferred Flow Direction) [No Unit]	0.15

The calibration process requires several important parameters for evaluation, such as NSE (Nash-Sutcliffe Efficiency), RMSE (Root Mean Square Error), PBIAS (Percent Bias), and MAPE (Mean Absolute Percentage Error) which are used to ensure the resulting model is accurate and suitable for the observed data. Each parameter has criteria that indicate the accuracy of the data. Based on these criteria, it can be seen that the simulation data and observation data match so that it can be seen that the modelling has represented the actual conditions.

NSE is a coefficient that can show the observed data and simulation results match. NSE value criteria can be seen in Table 2. The NSE formula is as follows:

The RMSE formula is as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Qobs - Qsim)^2}$$

Notes:
Qsim: Simulation discharge
Qobs: Observation discharge
n : Total data

RESULTS AND DISCUSSIONS

Sensitivity analysis is conducted by comparing simulation and observation results in the streamflow gauge comparison tool. Soil Water Capacity (SWC) refers to the maximum amount of water that can be retained by the soil within the root zone. An SWC value approaching 1000 mm results in lower simulated streamflow, which closely aligns with observed data, yielding a Nash-Sutcliffe Efficiency (NSE) value of 0.68. Conversely, an SWC value approaching 100 mm produces higher simulated streamflow with a corresponding NSE value of 0.59. These findings indicate that higher SWC values enable greater water retention within the root zone, whereas lower SWC values limit this capacity. Insufficient SWC reduces the

Table 3. Adjustments to SWC Values

SWC	NSE	RMSE	PBIAS	R^2(%)	MAPE
SWC 1000 mm	0.68	13.30	12.17	0.38	0.25
SWC 700 mm	0.66	15.65	16.31	0.27	0.34
SWC 500 mm	0.64	18.47	20.20	0.16	0.42
SWC 200 mm	0.59	26.70	29.30	-0.09	0.61

soil's ability to store water, thereby negatively impacting baseflow and soil moisture estimations, and leading to increased surface runoff. The calibrated SWC parameter values are presented in Table 3.

The graph depicting the relationship between Soil Water Capacity (SWC) and the Nash-Sutcliffe Efficiency (NSE) illustrates notable changes resulting from the trial-and-error adjustment of SWC values. An SWC value of 1000 mm shows an increasing trend in model performance, with the NSE rising to 0.68. In comparison, an SWC value of 700 mm results in a decreased NSE of 0.66, while a value of 500 mm further lowers the NSE to 0.64. A value of 200 mm leads to a more substantial decline in model performance, with the NSE dropping to 0.59. These results indicate that higher SWC values enhance model reliability, whereas lower SWC values reduce the model's ability to accurately represent existing hydrological conditions. The trend in SWC variation relative to NSE is presented in Figure 3.

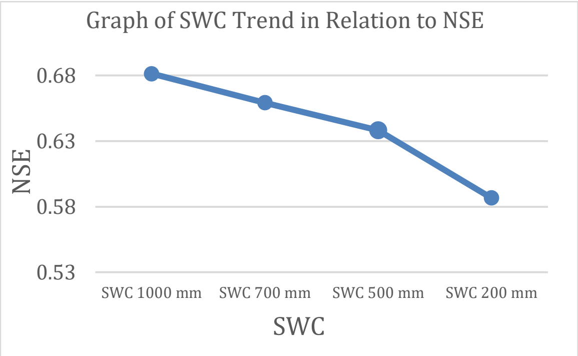

Figure 3 Graph of SWC Trend in Relation to NSE

Z1 is a parameter that represents the depth from which plant roots are able to extract water from the soil. As the value of Z1 decreases, the simulated discharge becomes closer to the observed data, with an NSE value of 0.65. In contrast, increasing the Z1 value results in higher simulated discharge, with a corresponding NSE of 0.54. This indicates that a relatively low Z1 corresponds to a limited storage capacity in the root zone. Conversely, a higher Z1 leads to an overestimation of soil water storage, as reflected by the calibration results, where the R^2 value becomes negative and shows no meaningful correlation. Furthermore, a higher Z1 increases surface runoff. The variation in the Z1 parameter is presented in Table 4.

The graph of Z1 against NSE indicates changes occurring through a trial and error process with varying Z1 values. A Z1 value of 0 shows an increasing trend in NSE, reaching 0.65. Conversely, a Z1 value of 50 results in a decrease in NSE to 0.62. At Z1 = 70, the NSE value further declines to 0.59. When Z1 reaches 100, the NSE performance continues to decrease, dropping to 0.54. Therefore, smaller Z1 values correspond to better model performance, whereas larger Z1 values indicate that the model does not adequately represent the existing conditions. The trend of changes in Z1 relative to NSE is illustrated in Figure 4.

Table 4. Adjustments to Z1 Values

Z1	NSE	RMSE	PBIAS	R^2(%)	MAPE
Z1 100%	0.54	33.61	30.57	-0.18	0.64
Z1 70%	0.59	25.80	25.86	0.02	0.54
Z1 50%	0.62	21.68	22.92	0.11	0.48
Z1 0%	0.65	15.18	16.66	0.21	0.35

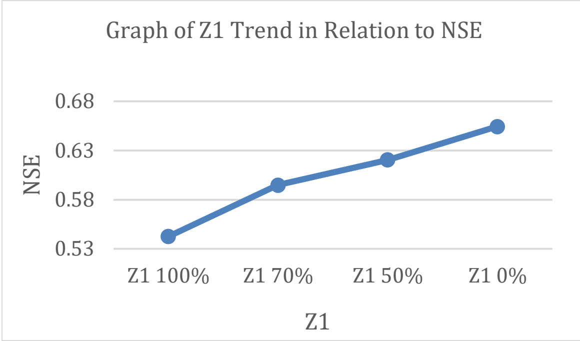

Figure 4 Graph of Z1 Trend in Relation to NSE

Z2 represents the water storage capacity in the deep zone. Changes in Z2 that are smaller correspond more closely to the observed values. Conversely, larger Z2 values result in simulation outputs that deviate further from the observations. However, variations in Z2 do not produce significant changes. This is evident from the parameter results, where a small Z2 value yields an NSE of 0.7, while a relatively large Z2 results in an NSE of 0.67. Based on the calibration results, a Z2 value of 0% provides the best simulation performance, with the highest NSE and R^2 values, as well as the lowest RMSE, PBIAS, and MAPE values. This suggests that the soil has a low deep storage capacity, causing most of the incoming flow to become direct runoff. The changes in the Z2 parameter are presented in Table 5.

Table 5. Adjustments to Z2 Values

Z2	NSE	RMSE	PBIAS	R^2(%)	MAPE
Z2 100%	0.67	14.33	24.05	0.39	0.50
Z2 70%	0.69	11.03	15.59	0.42	0.32
Z2 50%	0.70	9.62	10.63	0.43	0.22
Z2 0%	0.70	8.42	2.78	0.43	0.06

The graph of Z2 against NSE shows changes occurring through a trial and error process with varying Z2 values. A Z2 value of 0 indicates an increasing trend, with the NSE reaching 0.70. Meanwhile, a Z2 value of 50 exhibits a stable trend, maintaining an NSE of 0.70. At Z2 = 70, the NSE value decreases slightly to 0.69. When Z2 reaches 100, the NSE performance further declines to 0.67. Thus, smaller Z2 values indicate better model performance, whereas larger Z2 values suggest that the model does not adequately represent the existing conditions. The trend of changes in Z2 relative to NSE is illustrated in Figure 5.

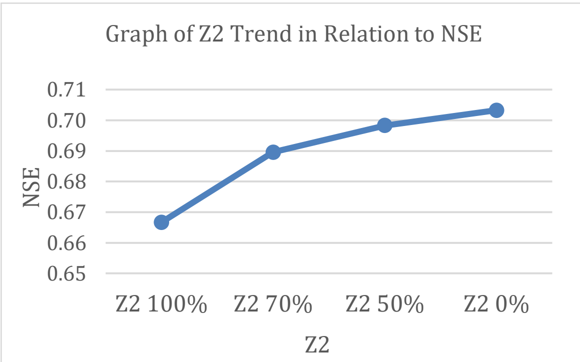

Figure 5 Graph of Z2 Trend in Relation to NSE

PFD is a parameter that represents the proportion of water percolating from the root zone to the deep zone. A decrease in the PFD value results in a closer match with the observed data. In contrast, higher PFD values lead to greater deviations between the simulation and observations. This is reflected in the RMSE values, where PFD = 1 yields an RMSE of 9.05, while PFD = 0.05 results in a lower RMSE of 8.36. A lower PFD value indicates that less water infiltrates into the deeper soil layers, thereby increasing surface runoff and reducing baseflow. The changes in the PFD parameter are presented in Table 6.

Table 6. Adjustments to PFD Values

PFD	NSE	RMSE	PBIAS	R^2	MAPE
PFD 1	0.71	9.05	8.87	0.42	0.18
PFD 0.7	0.71	8.80	6.65	0.42	0.14
PFD 0.15	0.70	8.42	2.78	0.43	0.06
PFD 0.05	0.70	8.36	2.10	0.44	0.04

The graph of PFD against NSE shows changes resulting from a trial and error process applied to different PFD values. A PFD value of 1 indicates an increasing trend, with the NSE reaching 0.71. A PFD value of 0.7 maintains a stable trend, also resulting in an NSE of 0.71. At PFD = 0.15, the NSE value slightly decreases to 0.70, while at PFD = 0.05, the NSE performance further declines to 0.70. Therefore, based on the NSE parameter, higher PFD values indicate better model performance, whereas lower PFD values suggest that the model does not adequately represent existing conditions. The trend of changes in PFD in relation to NSE is illustrated in Figure 6.

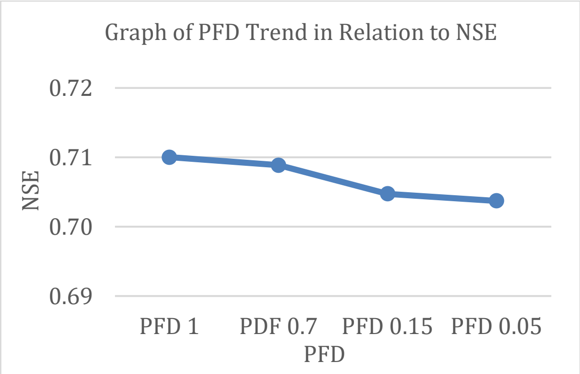

Figure 6 Graph of PFD Trend in Relation to NSE

RZC (Root Zone Conductivity) refers to the maximum capacity of the plant root zone to retain water. This parameter influences the soil's ability to hold rainfall before percolation or surface runoff occurs. Changes in RZC affect the NSE value, where larger RZC values lead to improved simulation results that more closely align with field conditions. This can be observed in the parameter variation, where RZC = 300 results in an NSE of 0.76, indicating improved model performance. A higher RZC value reflects greater soil capacity for water retention. In contrast, an RZC value of 20 yields an NSE of 0.70, suggesting that the simulation deviates from the observed data. The changes in the RZC parameter are presented in Table 7.

Table 7. Adjustments to RZC Values

RZC	NSE	RMSE	PBIAS	R2	MAPE
RZC 300	0.76	6.53	1.82	0.70	0.04
RZC 100	0.73	7.42	0.22	0.57	0.00
RZC 50	0.71	7.91	0.52	0.50	0.01
RZC 20	0.70	8.36	2.10	0.44	0.04

The graph of RZC against NSE demonstrates changes resulting from the trial and error process applied to varying RZC values. An RZC value of 300 indicates an increasing trend, with the NSE reaching 0.76. In contrast, an RZC value of 100 shows a declining trend, with the NSE decreasing to 0.73. At RZC = 50, the NSE further decreases to 0.71, while RZC = 20 results in a continued decline in model performance, with an NSE of 0.70. Therefore, based on the NSE parameter, higher RZC values indicate better model performance, whereas lower RZC values suggest that the model does not adequately represent existing conditions. The trend of RZC changes in relation to NSE is illustrated in Figure 7.

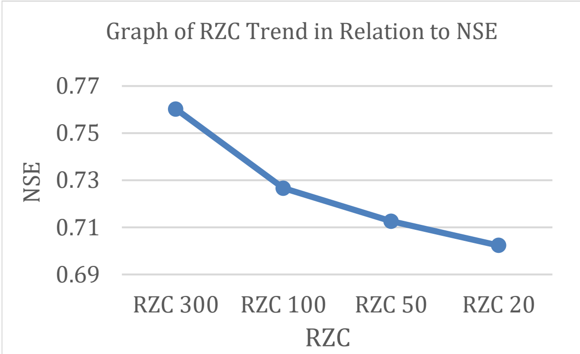

Figure 7 Graph of RZC Trend in Relation to NSE

DC is used to regulate the rate of water infiltration into the deeper soil layers. A high DC value indicates a greater deviation from the observed data, as evidenced by the comparison between simulation and observation results, with an RMSE value of 8.56. In contrast, lower DC values correspond more closely to observations, as reflected by a lower RMSE value of 6.53. A smaller DC value suggests that water infiltrates less easily into the deeper soil layers, resulting in increased surface runoff. The changes in the DC parameter are presented in Table 8.

Table 8. Adjustments to DC Values

DC	NSE	RMSE	PBIAS	R^2	MAPE
DC 400	0.78	8.56	28.09	0.65	0.59
DC 250	0.78	7.90	25.68	0.67	0.53
DC 100	0.79	6.96	18.63	0.71	0.39
DC 20	0.76	6.53	1.82	0.70	0.04

The graph of DC against NSE shows variations resulting from a trial and error process applied to different DC values. A DC value of 400 indicates an increasing trend, with the NSE reaching 0.78. Meanwhile, a DC value of 250 exhibits a stable trend, maintaining an NSE of 0.78. At DC = 100, the NSE increases further to 0.79. However, a DC value of 20 results in a decline in performance, with the NSE decreasing to 0.76. Thus, based on the NSE parameter, DC exhibits a fluctuating trend. The trend of changes in DC relative to NSE is illustrated in Figure 8.

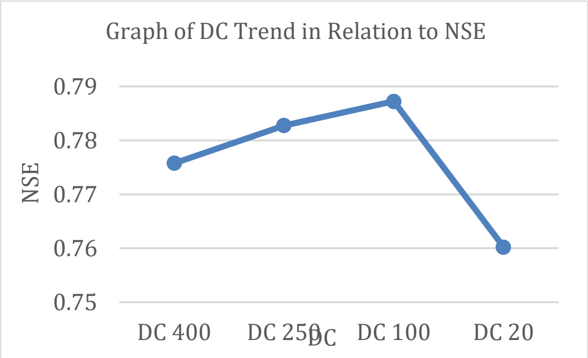

Figure 8 Graph of DC Trend in Relation to NSE

RRF is a parameter that controls the proportion of rainfall that directly becomes runoff. Higher RRF values result in simulated streamflow that closely matches observed data, as indicated by an NSE value of 0.85. Conversely, lower RRF values cause the simulation to deviate from observations, with the NSE decreasing to 0.78. A high RRF value increases runoff, leading to simulated discharge that more accurately reflects actual conditions. In contrast, a low RRF value causes more water to be retained in the soil, reducing runoff and leading to an overestimation of streamflow. Changes in the RRF parameter are presented in Table 9.

Table 9 Adjustments to RRF Values

RRF	NSE	RMSE	PBIAS	R^2	MAPE
RRF 10	0.85	5.35	19.99	0.84	0.42
RRF 5	0.84	5.39	20.74	0.81	0.43
RRF 2	0.78	7.90	25.68	0.67	0.53

The graph of RRF against NSE demonstrates changes resulting from the trial and error process applied to different RRF values. An RRF value of 10 shows an increasing trend, with the NSE reaching 0.85. Meanwhile, an RRF value of 5 indicates a decreasing trend, with the NSE dropping to 0.84. At RRF = 2, the NSE further decreases to 0.78. Thus, based on the NSE parameter, higher RRF values indicate better model performance, while lower RRF values suggest that the model does not adequately represent existing conditions. The trend of RRF changes in relation to NSE is illustrated in Figure 9.

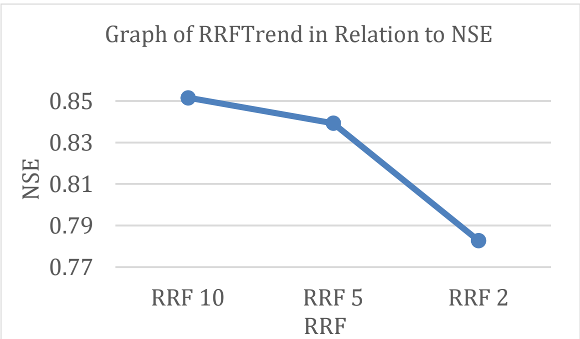

Figure 9 Graph of RRF Trend in Relation to NSE

DWC represents the water storage capacity in the lower and deep soil layers. Higher DWC values correspond to increased NSE results, reaching up to 0.85. Elevated DWC values yield simulations that closely match the observed data. Conversely, lower DWC values tend to produce NSE results that deviate from observations, with an NSE of 0.82 recorded at DWC = 400. A high DWC value accelerates percolation into the deep zone and increases surface runoff, thereby enhancing the agreement between simulated and observed discharge. Changes in the DWC parameter are presented in Table 10.

Table 10. Adjustments to DWC Values

DWC	NSE	RMSE	PBIAS	R2	MAPE
DWC 1000	0.85	5.35	19.99	0.84	0.42
DWC 600	0.84	7.18	24.82	0.79	0.52
DWC 400	0.82	8.64	26.81	0.74	0.56

The graph of DWC against NSE illustrates changes resulting from the trial and error process applied to different DWC values. A DWC value of 1000 indicates an increasing trend, with the NSE reaching 0.85. In contrast, a DWC value of 600 shows a declining trend, with the NSE decreasing to 0.84. At DWC = 400, the NSE further decreases to 0.82. Thus, based on the NSE parameter, higher DWC values indicate better model performance, whereas lower values suggest that the model does not adequately represent existing conditions. The trend of changes in DWC relative to NSE is presented in Figure 10.

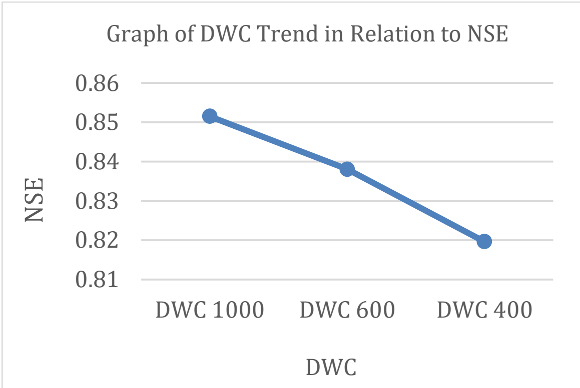

Figure 8 Graph of DWC Trend in Relation to NSE

Based on the sensitivity test process, the results obtained will be used for modelling. These results are considered feasible because they have similarities in the field according to observational data. Calibration analysis uses various method approaches to assess the extent to which the model can provide accurate and relevant predictions. The methods used include Nash-Sutcliffe Efficiency (NSE), Percentage Bias (PBIAS), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). The model interpretation results can be seen in Table 11. The optimum parameters used for modelling can be seen in the Table 12.

Table 12. The Model Interpretation Results

Parameter	Nilai	Interpretation
NSE	0.85	Good
RMSE	5.35	Good enough
PBIAS	19.99	Good enough
R^2	0.84	Medium influence
MAPE	0.42	Very accurate

Table 13. The Parameter Values Used

Parameter	Value Used
Z1 [%]	0
Z2 [%]	0
DWC (Deep Water Capacity) [mm]	1000
DC (Deep Conductivity) [mm/month]	250
RRF (Resistance Runoff Factor) [No Unit]	10
RZC (Root Zone Conductivity) [mm/month]	300
SWC (Soil Water Capacity) [mm]	1000
PFD (Preferred Flow Direction) [No Unit]	0.05

The NSE of 0.825 indicates that the model can approach the observed discharge well. The model can explain most of the fluctuations that occur in the observed discharge data. NSE values of more than 0.75 are generally considered very good, which means that the model can accurately describe the movement of discharge. These results show that despite some differences between the simulated and observed discharge the model can reflect the patterns and trends present in the observed data very well.

The Root Mean Squared Error (RMSE) value obtained in this analysis, which is 5.35 indicates a relatively good agreement between the model simulation results and the field observation data. Although there are variations, the recorded RMSE value reflects the level of error that is still within acceptable tolerance limits, so this model can be considered representative enough to resemble the actual discharge conditions.

The PBIAS value of 19.99% indicates that the model tends to overpredict the simulated discharge compared to the observed discharge. In other words, the model predicts a discharge about 19.99% larger than the observed data. The PBIAS value falls into the moderate category.

The R^2 value of 0.84 indicates that the model successfully explains 84% of the variability in observed discharge. This means that the model can capture most of the patterns present in the discharge data, although there is still 16% of the variation that cannot be explained by the model. In other words, the model is good enough to explain the overall variability of the observed discharge.

The MAPE of 0.42% indicates that the model has a very low prediction error in percentage. In other words, although there is a bias in the absolute discharge value (as seen in PBIAS), the model is very accurate in its relative prediction. This very low MAPE indicates that the predicted discharge by the model tends to be very close to the observed value when measured in terms of relative error. The model interpretation results can be seen in the Table 12.

The comparison graph of simulated and observed discharge for the year 2014 demonstrates a well-aligned trend pattern, particularly in capturing periods of high and low flow. In the early months (January–March), both observed and simulated discharges show relatively high values, with minor fluctuations that remain within an acceptable error range. From April to October, there is a significant decrease in discharge, consistent with the dry season pattern, during which flow tends to be low. Subsequently, in November and December, both observed and simulated data exhibit a sharp increase in discharge. This rise reflects the onset of the rainy season, and the model is able to closely follow the upward trend. The similarity in patterns between the observed and simulated results indicates that the model performs well in representing actual hydrological conditions, despite some discrepancies in the magnitude of discharge values. The results of the analysis using the optimum parameter values produce a comparison graph of observation and simulation discharge which can be seen in the Figure 9.

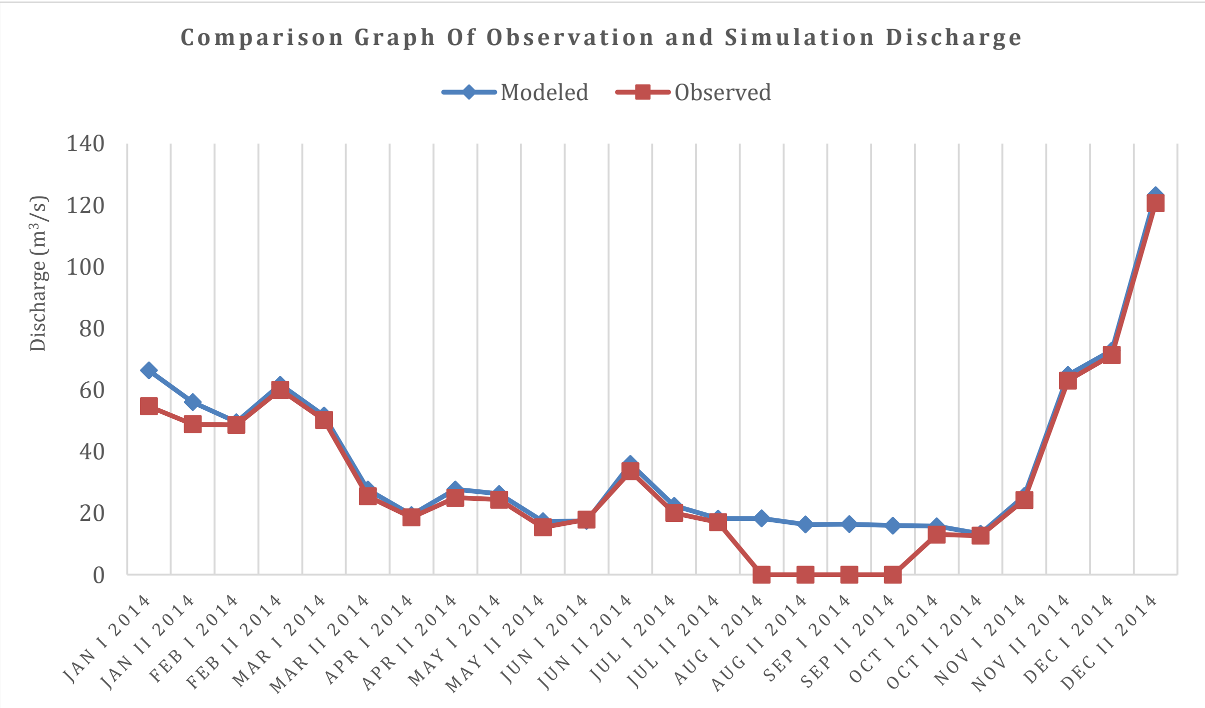

Figure 9 Comparison Graph of Observation and Simulation Discharge

CONCLUSIONS

1. During the sensitivity analysis of various calibration parameters in the WEAP model, certain parameters exhibited similar behaviour. Specifically, SWC, RZC, and DWC showed a direct relationship with NSE values. It means that as these parameter values increased, the resulting NSE values also increased. In contrast, Z1, Z2, PFD, DC, and RRF demonstrated an inverse relationship, where higher parameter values corresponded to lower RMSE values
2. The calibration process involved adjusting several parameters to optimize model performance as measured by the Nash-Sutcliffe Efficiency (NSE). The parameter SWC was assigned a value of 1000, resulting in an NSE of 0.68. Both Z1 and Z2 were set to 0, yielding NSE values of 0.65 and 0.70, respectively. The PFD parameter, calibrated at 0.05, produced an NSE of 0.70. The RZC parameter was set to 300, achieving an NSE of 0.76, while the DC parameter, fixed at 250, resulted in an NSE of 0.78. Notably, the RRF parameter, with a value of 10, attained a higher NSE of 0.85. Similarly, the DWC parameter set at 1000 also reached an NSE of 0.85. These results indicate progressive improvements in model accuracy corresponding to the adjustment of these parameters
3. Based on the optimum parameters, the interpretation of the NSE model is 0.85 in the good category. The RMSE value is 5.35 in the good enough category. PBIAS value is 19.99 in the good enough category. The R^2 value is 0.84 in the medium influence category. While the MAPE value is 0.42 in the very accurate category. So that this modelling represents the actual conditions
4. Future research is recommended to apply the WEAP model in other locations to evaluate its adaptability and robustness across different hydrological settings. Moreover, integrating spatial planning data such as RTRW (Regional Spatial Planning) that accounts for annual land use changes could enhance the model's accuracy and provide more detailed simulations over time

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