




## Improvement and Analysis for Accuracy of Baseflow Using SWAT-CUP Premium in the Yongjeon Stream, South Korea

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**Abstract**—Here, the results of Soil and Water Assessment Tool (SWAT) simulation are calibrated and validated using SWAT-CUP Premium, and the  $R^2$  (coefficient of determination) values of simulated and observed flows are compared. According to the SWAT analysis of the Cheongsong Yongjeon stream basin, low accuracy of 0.40 was the  $R^2$  value for simulated and observed flows, and the baseflow was calculated at an annual average of 46.659 m<sup>3</sup>/s. During the same period, after calibration and validation using SWAT-CUP Premium, the  $R^2$  value of simulated and observed flows was improved to 0.71, and the evaluation indexes showed 0.51 for Nash–Sutcliffe efficiency (NS), 37.1 for percent bias (PBIAS), 0.73 for P-factor, and 0.33 for R-factor, indicating that the relationship between observed and simulated flows was improved. In addition, after calibration and validation, the baseflow was 56.951 m<sup>3</sup>/s, which was a more accurate value than the one before calibration and validation.

**Keywords:** SWAT-CUP Premium, baseflow, coefficient of determination, simulated flow.

### 1. Introduction

Recently, due to climate change and urbanization, rainfall patterns and infiltration rates have changed, which has led to a decrease in the groundwater levels and stream drying, causing problems in supply of water resources. In particular, a reduction in infiltration due to urbanization can lead to a reduction in groundwater levels and underlying runoff, and a decrease in baseflow rate can affect the supply of stream flow during the dry season. For this reason,

accurate analysis and verification of baseflow is essential. However, difficulty in integrated interpretation, considering surface water–groundwater interaction, uncertainty about analysis of baseflow runoff, and technical limitations make the analysis of baseflow challenging.

Since baseflow runoff is affected not only by rainfall and flow rate but also by groundwater flowing into and out of aquifers, it is closely related to groundwater recharge, and it is necessary to differentiate between direct runoff and baseflow runoff to understand the characteristics of baseflow runoff (Aizen et al., 2000; Ferket et al., 2010). Baseflow runoff separation has been widely studied, including master groundwater depletion curve, straight line, fixed base, and variable slope methods, and interpretation using watershed hydrological modeling is currently a dominant technique.

Managing baseflow is crucial to ensuring a stable water supply when water resources are not sufficient. However, unlike direct runoff, there is a lack of measured data on baseflow due to various difficulties such as measurement time, equipment, and technology. Therefore, many techniques have been developed and used to analyze baseflow. A baseflow analysis is usually performed by separating direct runoff from baseflow using hydrographs and analyzing baseflow using watershed-scale models. However, separating baseflow using hydrographs cannot be efficiently applied to long-term runoff, and there are also difficulties in objective baseflow separation during the process. Therefore, watershed-scale runoff models such as the Hydrological Simulation Program—FORTRAN (HSPF), Soil and Water Assessment Tool (SWAT), and Precipitation-Runoff Modeling System, version 4 (PRMS-IV) are used to

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estimate baseflow runoff (Caldwell et al., 2015; Dams et al., 2015; Gay et al., 2023).

In particular, the SWAT model is the most frequently used model for interpreting baseflow runoff among rainfall-runoff models (Ligaray et al., 2015; Rouholahnejad et al., 2014; Veetil & Mishra, 2016).

Arnold et al. (2000) estimated groundwater recharge in the Mississippi River basin using the SWAT model and evaluated baseflow runoff through it. A study was also conducted to simulate baseflow runoff using the SWAT model and compare the results (Abbaspour et al., 2007; Luo et al., 2012). In addition, a scenario-specific analysis of climate change, such as temperature and precipitation, and a baseflow runoff analysis according to changes in soil conditions and land use were conducted (Duan et al., 2017; Zhang & Schilling, 2006). An analysis of stream runoff and baseflow runoff was also conducted for river basin management (Aboelnour et al., 2020; Dechmi et al., 2012).

Srinivasan et al. (2010) applied the SWAT model to simulate various hydrological components, including baseflow, to analyze the water balance for ungauged basins in the upper Mississippi River basin and predict crop yield. Andrianaki et al. (2019) used the SWAT model to analyze changes in runoff from precipitation and glaciers, and compared the uncertainties according to scenarios. Many studies have also been conducted to perform effective hydrological analysis while minimizing parameter uncertainties and suggesting the most sensitive parameters (Hosseini & Khaleghi, 2020; Khatun et al., 2018; Malik et al., 2022; Sao et al., 2020). In particular, some studies have analyzed the change in baseflow and scenarios according to urbanization and changes in land use (Aboelnour et al., 2019), and other studies have calibrated and validated stream flow estimations using the SWAT model and SWAT-CUP (Hallouz et al., 2018; Jaiswal et al., 2020; Vilaysane et al., 2015).

However, previous studies have mostly focused on analyzing the baseflow index. Therefore, there is a lack of research on the effective management of water resources and quantitative baseflow estimates after improving model uncertainties. Since the SWAT model has many parameters related to each

hydrological element, calibration and validation are crucial.

Baseflow in rivers is influenced by rainfall, river flow, and groundwater flowing in and out of aquifers. These different factors converge to enable the circulation of water, with groundwater being a significant source for supplementing river water. Therefore, as various hydrological and water resources-related analysis models are currently used for hydrological analysis, enhancing the accuracy and reliability of their simulations is imperative. If we have a highly accurate hydrological analysis model, it can be utilized to compare and analyze the correlation between baseflow and groundwater fluctuations in order to infer baseflow trends. It can also be used to ensure the efficient use of water resources, enhanced research and development (R&D), more accurate groundwater level forecasting, and better management and conservation in areas where water resources are scarce (such as the study area).

The study area in question is a small rural area that is in need of effective agricultural water management due to water scarcity. Due to these conditions, baseflow and runoff analysis using groundwater is essential. Therefore, the long-term goal of this study is to integrate the surface water and groundwater factors to better enable baseflow and water reserve analysis. This analysis is necessary for providing accurate forecasting during the dry period. To this end, SWAT simulation results were calibrated and validated using SWAT-CUP Premium, and  $R^2$  values of simulated and observed flows were compared. The accuracy of the simulation results was also improved by comparing the baseflow before and after calibration and validation.

## 2. Study Area and Methods

The aim of this study is to improve the accuracy of baseflow and to analyze the uncertainty of baseflow by calculating baseflow and performing calibration and validation using the SWAT model. The SWAT model is a semi-distributed rainfall-runoff model, which can be run daily. Apart from runoff and sediment, it can also simulate pollution.

The Soil and Water Assessment Tool (SWAT) is a model developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS). It is used to estimate the impact of land management practices on the behavior of runoff, sediment discharge, and agricultural chemicals in large, complex watersheds, depending on various soil properties, long-term land use, and land management conditions. SWAT is basically composed of four sub-models: hydrology, soil loss, nutrients, and channel tracking (Arnold et al., 1998).

The SWAT model divides the target watershed into several subbasins to reflect the different surface characteristics of the watershed, and is subdivided into hydrological response units (HRU) that exhibit similar characteristics within the subbasin.

However, models that require various input data and parameters, such as SWAT, have difficulty presenting simulation results. In particular, parameters based on the characteristics of the watershed must be accompanied by calibration and validation, as accurate estimation is difficult due to inaccuracies in observations. The calibration and validation of hydrological models is a process of finding the optimal parameters to simulate the hydrological characteristics of a watershed as closely as possible.

However, further analysis of calibration, validation, and uncertainty are essential because uncertainty exists regarding the simulation results. SWAT-CUP is a program developed by the EAWAG Institute in Switzerland for calibration, validation, and uncertainty analysis of the SWAT model. SWAT-CUP Premium is an improved version of SWAT-CUP that can improve uncertainty about results of SWAT simulation.

The program can select one of two algorithms, SWAT parameter estimator (SPE) or particle swarm optimization (PSO), and uses the selected algorithm to perform calibration and derive optimal parameters using exchange and relative parameter change methods within the range of parameters. SWAT-CUP Premium removes the generalized likelihood uncertainty estimation (GLUE), parameter solution (ParaSol), and Markov chain Monte Carlo (MCMC) algorithms, which are highly inefficient for running SWAT models, and instead uses the SPE algorithm, an upgraded sequential uncertainty fitting version 2

(SUFI-2) algorithm. Therefore, we used the SPE algorithm in this study. The SPE algorithm is a method used to estimate parameters sequentially. It consists of uncertain components such as parameters and measurements. The degree of all uncertainties is measured by a 95% confidence level uncertainty.

The study area is the Yongjeon stream basin in Cheongsong County, which is a local river with a watershed area of 381.0 km<sup>2</sup> and river length of 48.0 km. The Yongjeon stream consists of smaller streams, the third tributaries of the Nakdong River, including the Singi, Sinheung, Jubang, Jusan, Nobu, Kwaee, and Gupyeong streams. The left bank of Yongjeon stream is a basin with a narrow watershed width, and the right bank basin is widely developed, located at 129° 54' 44"–129° 13' 50" east longitude and 36° 13' 18"–36° 30' north latitude. The input data for simulation were analyzed using weather data (Cheongsong Weather Station, Juwang Mountain Weather Station) and measured data (Cheongsong Water Level Gauge Station) from the observatories located in the basin (Fig. 1).

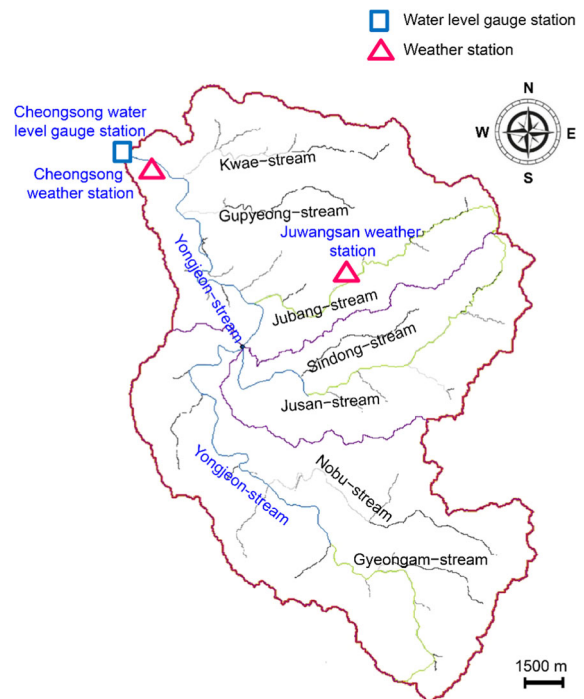


Figure 1  
Location of streams and weather stations in study area

The geology of the study area consists of plutonic, sedimentary, andesitic, granitic, and acidic volcanic rocks, and alluvium (Fig. 2). Plutonic rocks contain many pink feldspars and have a coarse to medium granular texture. The main constituent minerals are quartz, orthoclase, microcline, plagioclase, and biotite. In addition, small amounts of hornblende and magnetite are distributed.

### 3. SWAT Analysis and Accuracy Improvement

#### 3.1. Input Data for SWAT Model

The input data for the SWAT model include weather data, digital elevation data, and land use,

soil, and groundwater information. In the case of weather data, the input data for the model was constructed using data from weather stations located in the study area. Figure 3a shows digital elevation data in the study area and smaller streams divided into three. Medium scales (1:25,000) of land use map were utilized; the largest distribution was of forest areas (82.5%), and distribution of farmland, including rice paddies and fields, was about 14.3% (Fig. 3b). A 1:25,000 scaled soil map was used. Figure 3c provides the simulated spatial distribution of the precision soil map of Yongjeon stream like the prior land use map with the same spatial resolution as the digital elevation model. There are 50 types of soil

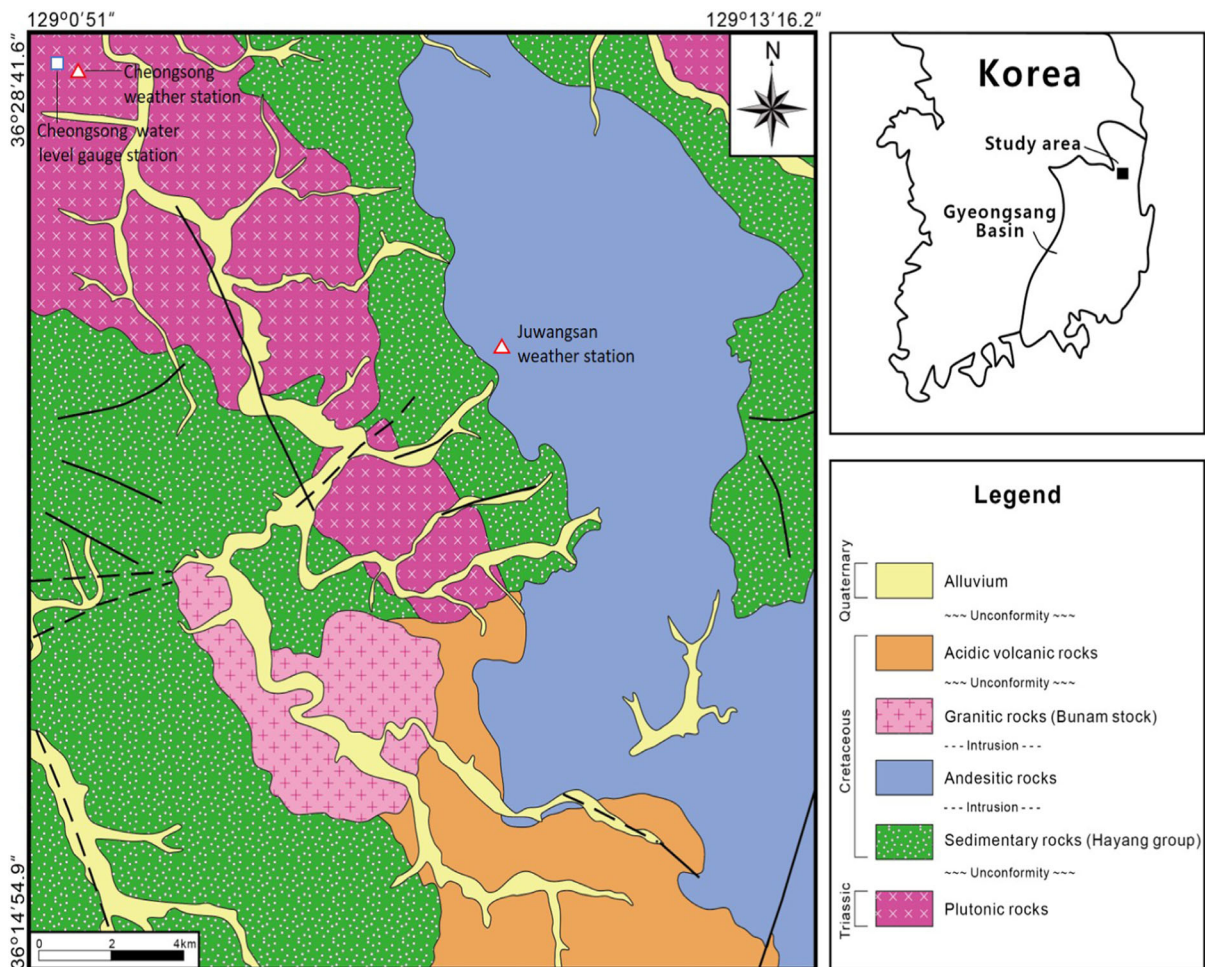


Figure 2  
Geological map of the study area

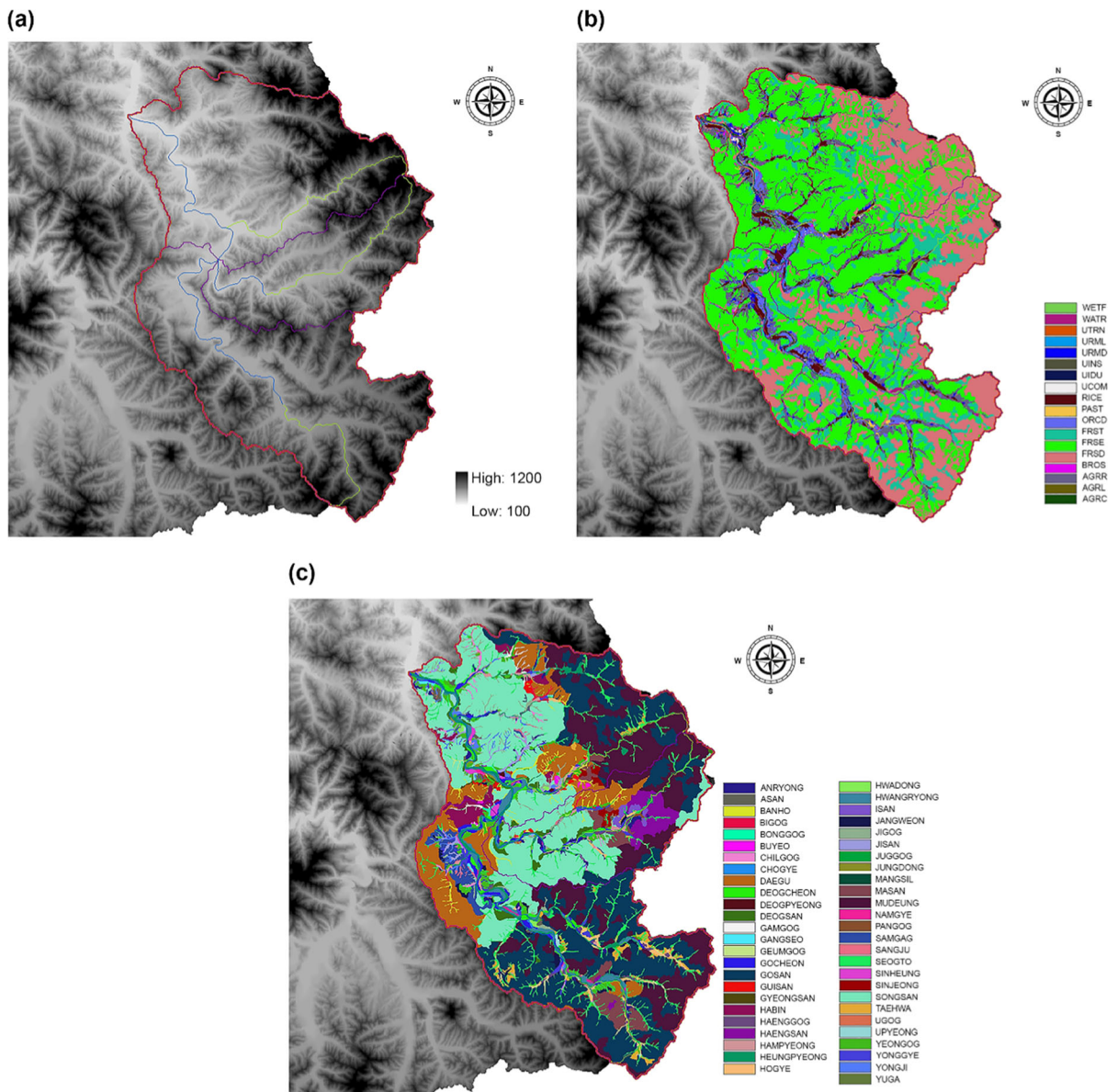


Figure 3  
Input data for SWAT analysis. **a** Digital elevation model. **b** Land use map. **c** Soil map

series, and information on the area of each soil series is shown in Tables 1 and 2.

### 3.2. SWAT Analysis

The input data for the SWAT model was constructed using available meteorological data for the study area that spanned the years from 2011 to

2019. Because some of the flow data from the Cheongsong water level data from 2017 to 2019 was missing (because measurements were not taken), the SWAT simulation was conducted using the input data from 2011 to 2016 instead. Since the first 2 years of data (those being from 2011 and 2012) were excluded to stabilize the SWAT model, the calibration and validation period for comparing actual observations

Table 1  
*Land use items and associated area of Yongjeon stream*

Land use classification item	Description	Area (km <sup>2</sup> )	Ratio (%)
URMD	Residential-medium density	2.87	0.94
UIDU	Industrial	0.04	0.01
UCOM	Commercial	0.33	0.11
UTRN	Transportation	1.09	0.35
UINS	Institutional	0.16	0.05
RICE	Rice	8.35	2.72
AGRR	Agricultural land-row crops	23.71	7.73
URML	Residential-med/low density	0.05	0.02
ORCD	Orchard	9.26	3.02
AGRL	Agricultural land-generic	0.24	0.08
FRSD	Forest-deciduous	75.30	24.55
FRSE	Forest-evergreen	137.68	44.90
FRST	Forest-mixed	39.93	13.02
PAST	Pasture	0.33	0.11
BROS	Smooth brome grass	0.61	0.20
WETF	Wetlands-forested	1.18	0.38
AGRC	Agricultural land-close-grown	2.26	0.74
WATR	Water	3.26	1.07

Table 2  
*Area by soil type in Yongjeon stream*

Soil classification	Area (km <sup>2</sup> )	Ratio (%)	Soil classification	Area (km <sup>2</sup> )	Ratio (%)
ANRYONG	2.26	0.74	HWADONG	0.33	0.11
ASAN	0.95	0.31	HWANGRYONG	4.39	1.43
BANHO	2.59	0.85	ISAN	0.97	0.32
BIGOG	0.58	0.19	JANGWEON	2.20	0.72
BONGGOG	0.14	0.04	JIGOG	3.28	1.07
BUYEO	0.31	0.1	JISAN	1.80	0.59
CHILGOG	1.19	0.39	JUGGOG	0.08	0.03
CHOGYE	0.07	0.02	JUNG DONG	0.19	0.06
DAEGU	27.30	8.9	MASAN	6.25	2.04
DEOGCHEON	1.84	0.6	MUDEUNG	53.39	17.41
DEOGPYEONG	0.15	0.05	NAMGYE	0.44	0.14
DEOGSAN	2.97	0.97	PANGOG	0.20	0.07
GAMGOG	0.67	0.22	SAMGAG	3.63	1.18
GANGSEO	0.33	0.11	SANGJU	0.60	0.19
GEUMGOG	0.65	0.21	SEOGTO	12.11	3.95
GOCHEON	2.99	0.98	SINHEUNG	0.75	0.25
GOSAN	65.74	21.44	SINJEONG	1.31	0.43
GUISAN	0.90	0.29	SONGSAN	66.13	21.57
GYEONGSAN	0.13	0.04	TAEHWA	2.73	0.89
HABIN	4.75	1.55	UGOG	0.06	0.02
HAENGGOG	1.12	0.37	UPYEONG	0.34	0.11
HAENG SAN	5.16	1.68	YEONGGOG	6.85	2.23
HAMPYEONG	1.26	0.41	YONGGYE	2.01	0.66
HEUNGPYEONG	8.29	2.7	YONGJI	1.89	0.62
HOGYE	2.04	0.66	YUGA	0.36	0.12

and modeled values was a total of 4 years (spanning 2013–2016).

Figures 4 and 5 show a comparison graph of the SWAT analysis results and observed flow and

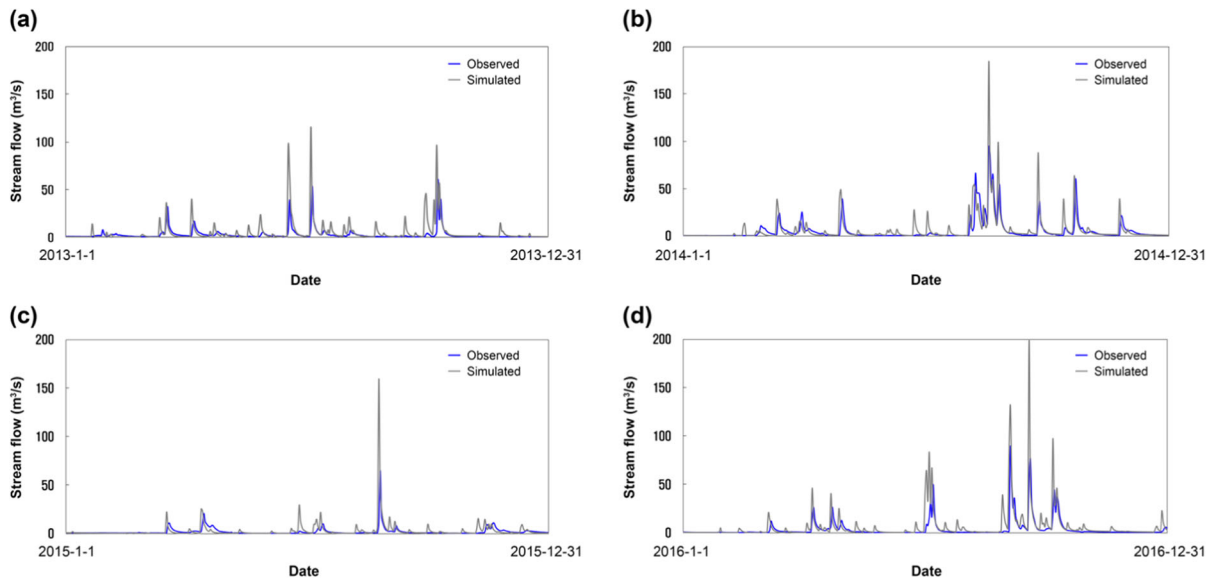


Figure 4

Comparison graph of simulated and observed flows (before calibration and validation): **a** 2013, **b** 2014, **c** 2015, **d** 2016

coefficient of determination ( $R^2$ ) for each year, and Fig. 6 shows the comparison results for the entire period (4 years). Results of the model analysis show that patterns were similar to observations according to precipitation, but the difference in flow rates was significant. The comparison of  $R^2$  values for simulated and observatory values showed that they were highest in 2014 (0.52). In 2015, they were low (0.17), and the  $R^2$  value for the entire period was 0.40, with very low accuracy.

#### 4. Calibration and Validation Using SWAT-CUP Premium

Studies have been conducted consistently to increase the prediction and accuracy of the SWAT model and improve the uncertainty of simulation results. Common techniques for calibration of parameters are MCMC (Vrugt et al., 2008), GLUE (Beven & Binley, 1992), PSO (Abbaspour, 2011), ParaSol (van Griensven & Meixner, 2007), and SUFI-2 (Abbaspour et al., 2004), and they can be easily applied in conjunction with the SWAT model using SWAT-CUP. SWAT-CUP Premium is a program that calibrates, validates, and improves SWAT

analysis results through algorithms such as SPE, which can be used to perform validation and sensitivity analysis (Fig. 7). Notably, SWAT-CUP Premium removes the GLUE, ParaSol, and MCMC algorithms, which are highly inefficient for running SWAT models, and instead uses the SPE algorithm, an upgraded SUFI-2 algorithm. Therefore, the SPE algorithm was used in this study. Table 3 provides a description for each algorithm.

In this study, SWAT-CUP Premium was used to perform calibration and validation, and 1000 simulations were performed during the calibration in consideration of the efficiency (Yu et al., 2020). In addition, the simulated flow was optimized with the SPE algorithm of SWAT-CUP Premium for the observed flow; the optimized parameter results are shown in Table 4.

The coefficient of determination ( $R^2$ ), Nash–Sutcliffe efficiency (NS), modified NS (MNS), and percent bias (PBIAS) were used to evaluate the simulation results with calibrated parameters. MNS,  $R^2$ , and NS were well matched, as they were closer to 1. The closer PBIAS was to zero, the better the observed and simulated values were matched (Gupta et al., 1999). Equation 1 shows the calculation of PBIAS, and in the case of the NS value, if it is 0.50 or

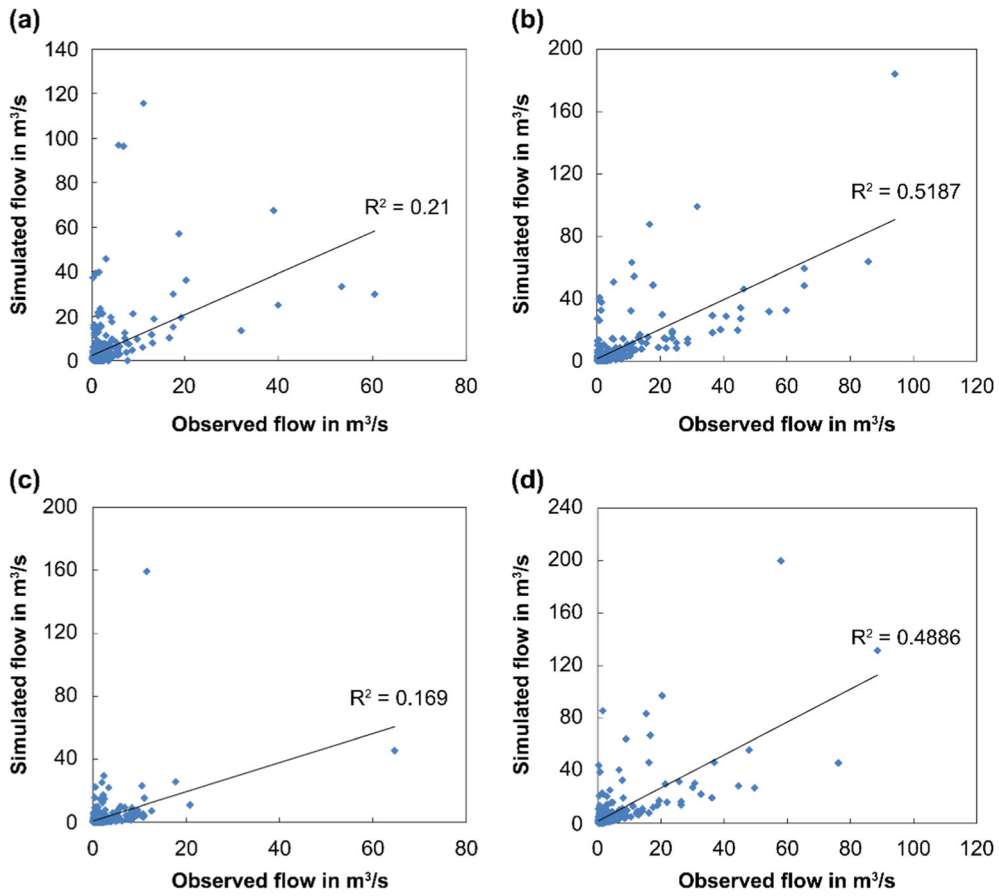


Figure 5

Comparison of  $R^2$  values for simulated and observed flows (before calibration and validation): **a** 2013, **b** 2014, **c** 2015, **d** 2016

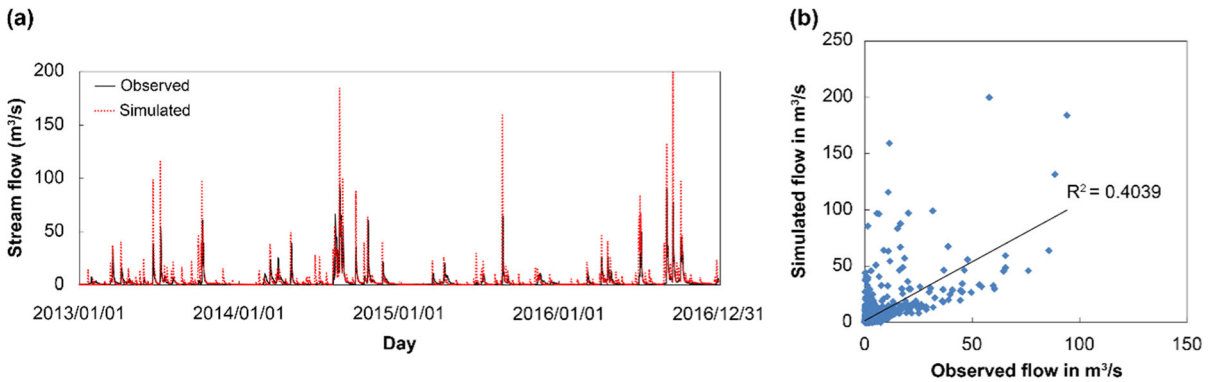


Figure 6

Comparison of simulated and observed flows for the entire study period (2013–2016) (before calibration and validation). **a** Comparison of observed and simulated flows. **b** Comparison of  $R^2$  values for observed and simulated flows



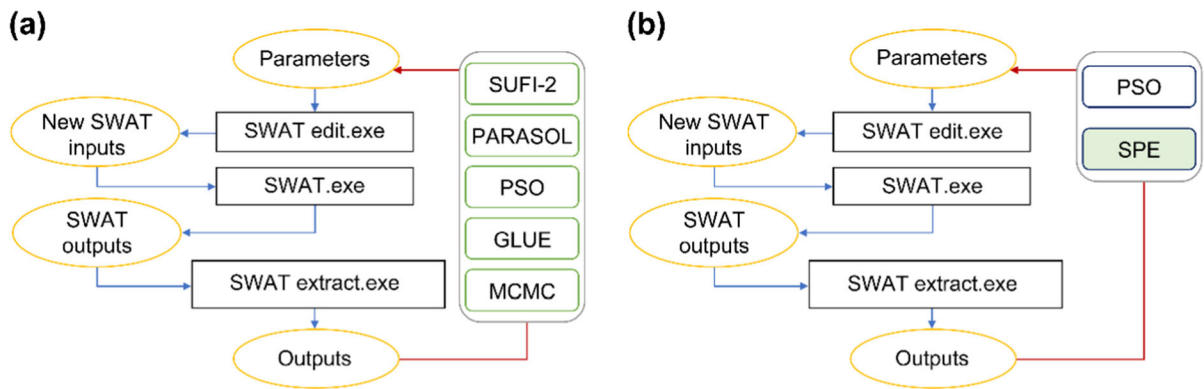


Figure 7

Schematic of SWAT-CUP and SWAT-CUP Premium (adapted from Abbaspour, 2011): **a** SWAT-CUP and **b** SWAT-CUP Premium

Table 3

The acronyms and descriptions for each algorithm

Acronym	Algorithm	Description
SUF2	Sequential uncertainty fitting ver.2	In SUFI-2, parameter uncertainty is described by a multivariate uniform distribution in a parameter hypercube (Abbaspour et al., 2004)
PSO	Particle swarm optimization	PSO is a popular optimizer in which each particle selects its learning exemplars relying on their fitness (Abbaspour, 2011)
GLUE	Generalized likelihood uncertainty estimation	GLUE is an uncertainty analysis technique inspired by importance sampling and regional sensitivity analysis (Beven & Binley, 1992)
ParaSol	Parameter solution	ParaSol is based on a modification to the global optimization algorithm SPE-UA (van Griensven & Meixner, 2007)
MCMC	Markov chain Monte Carlo	MCMC methods are a class of algorithms for sampling from probability distributions based on constructing a Markov chain that has the desired distribution as its equilibrium distribution (Vrugt et al., 2008)
SPE	SWAT parameter estimator	Upgraded SUFI-2 algorithm (adapted from Abbaspour, 2011)

Table 4

Maximum and minimum ranges and optimal parameter values for SWAT input parameters

Input	Parameter	Initial range	Initial value	Fitted value
Gw	ALPHA_BF	-0.048 to 0.952	0.653	0.316
Hru	CANMX	0-100	28	58.950
Rte	CH_K2	-0.01 to 500	155	294.746
Sub	CH_N1	-0.004 to 29.986	24	10.058
Rte	CH_N2	-0.024 to 0.286	0.128	0.065
Mgt	CN2	-0.25 to 0.25	0.12	-0.115
Hru	EPCO	0 to 1	0.143	0.350
Hru	ESCO	-0.95 to 0.05	-0.46	0.008
Gw	GW_DELAY	0-500	237	382.250
Gw	GW_REVAP	0.02-0.2	0.09	0.074
Gw	GWQMN	0-5000	4150	1327.500
Gw	RCHRG_DP	-0.05 to 0.95	0.425	0.844
Gw	REVAPMN	0-500	123	209.250
Bsn	SFTMP	-6 to 0	-4.3	-1.377
Hru	SLSUBBSN	10 to 150	86	-0.043
Bsn	SMFMN	-4.5 to 5.5	1.5	-4.355
Bsn	SMFMX	-4.5 to 5.5	2.7	0.445
Bsn	SMTMP	-0.20 to 20	0.7	1.22
Sol	SOL_AWC	-0.25 to 0.25	0.1	-0.004
Sol	SOL_K	-0.25 to 0.25	0.14	0.248
Sol	SOL_Z	-0.25 to 0.25	0.15	-0.227
Bsn	SURLAG	-3.95 to 20	11.45	3.175
Bsn	TIMP	-1 to 0	-0.050	-0.650

greater, it can be determined that the improvement effect on uncertainty is high, and can be expressed as shown in Eq. 2 (Nash & Sutcliffe, 1970).

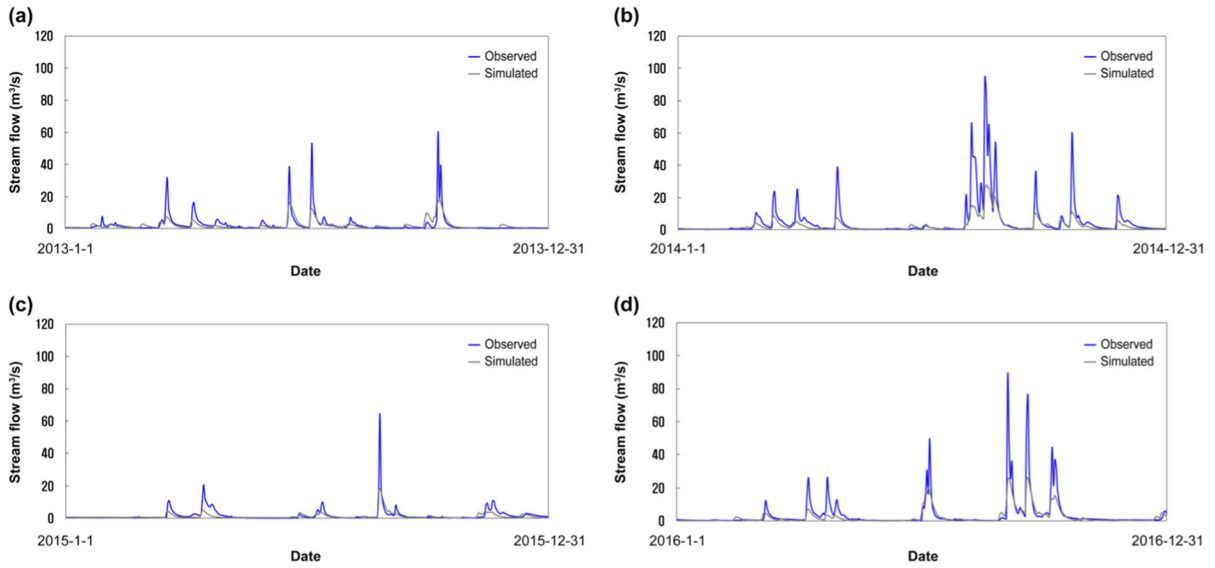


Figure 8

Comparison graph of simulated and observed flows (after calibration and validation): **a** 2013, **b** 2014, **c** 2015, **d** 2016

$$PBIAS = \frac{[\sum_{i=1}^n (O_i - S_i) * 100]}{[\sqrt{\sum_{i=1}^n (O_i)}]}, \quad (1)$$

where  $O_i$  is the observed values, and  $S_i$  is simulated values.

$$NS = 1 - \frac{\sum (O_o - O_s)^2}{\sum (O_o - \bar{O}_o)^2}, \quad (2)$$

where  $O_o$  is observed values,  $O_s$  is simulated values, and  $\bar{O}_o$  is average observed values.

In the SPE algorithm, uncertainty of the simulation results is quantified by 95 PPU (95% prediction uncertainty band). The 95 PPU is calculated with parameters, including a measured 95% prediction interval, based on which P- and R-factors are measured. The P-factor is an indicator of the percentage at which the observed values are included in the 95 PPU, and when the P-factor is 1, it means that the observed value is 100% included in the 95% prediction interval. On the contrary, the R-factor represents an average band width of 95 PPU; the closer the value is to zero, the better the calibration results coincide with the observed values. In general, for the simulation of runoff, if the P-factor is between 0.70 and 0.75, it is considered suitable.

Figures 8, 9, and 10 show graphs comparing the simulated results and observed flow using optimal parameters obtained by the SPE algorithm. The graphs showed that the tendency of daily and seasonal variability was well reproduced, and the flow level corresponding to each day was similar to others. Table 5 shows a comparison of  $R^2$  values before and after calibration and validation. The  $R^2$  value for SWAT analysis before calibration and validation is 0.40, but after calibration and validation using SWAT-CUP Premium, the simulation result was improved to 0.71. Table 6 shows the model performance evaluation, with NS of 0.51, PBIAS of 37.1, P-factor of 0.73, and R-factor of 0.33, indicating that the relationship between the observed and simulated flows has improved, which is considered to be well matched.

### 5. Baseflow Analysis and Comparison

To compare baseflow before and after calibration and validation, SWAT output data were used to extract surface water runoff (SURQ\_mm), intermediate runoff (LATQ\_mm), and groundwater runoff (GWQ\_mm) for the basin. The extracted data per unit

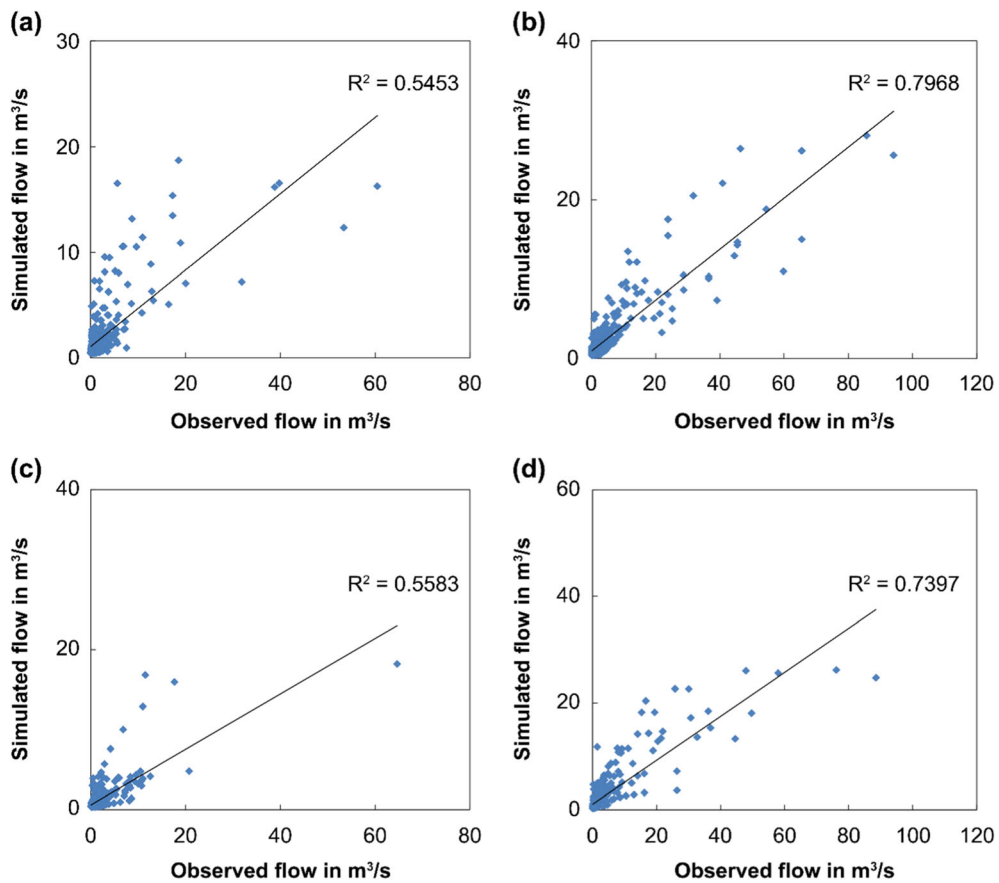


Figure 9  
Comparison of  $R^2$  values of simulated and observed flows (after calibration and validation): **a** 2013, **b** 2014, **c** 2015, **d** 2016

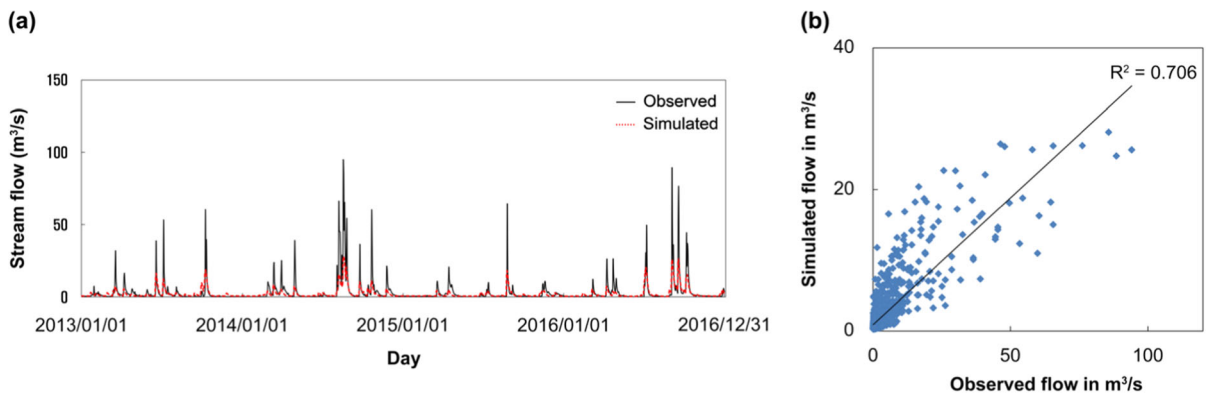


Figure 10  
Comparison of simulated and observed flow for the entire study period (2013–2016) (after calibration and validation). **a** Comparison of observed and simulated flows. **b** Comparison of  $R^2$  values of observed and simulated flows

area was calculated by runoff through unit conversion, and the baseflow was used for an intermediate

runoff and groundwater runoff. Table 7 and Fig. 11 show the results of the baseflow analysis for each

Table 5

Comparison of  $R^2$  values by year before and after calibration and validation

Year	2013	2014	2015	2016	2013–2016
Before calibration and validation (SWAT)	0.21	0.52	0.17	0.49	0.40
After calibration and validation (SWAT-CUP Premium)	0.55	0.80	0.56	0.74	0.71

Table 6

Simulation results using SWAT-CUP Premium after calibration and validation

Evaluation factor	$R^2$	NS	PBIAS	MNS	P-factor	R-factor
Simulation results	0.71	0.51	37.1	0.52	0.73	0.33

Table 7

Baseflow comparison before and after calibration and validation

Baseflow	2013	2014	2005	2016	Average
Before calibration and validation ( $\text{m}^3/\text{s}$ )	42.553	60.631	23.404	60.048	46.659
After calibration and validation ( $\text{m}^3/\text{s}$ )	52.533	73.446	28.764	73.060	56.951

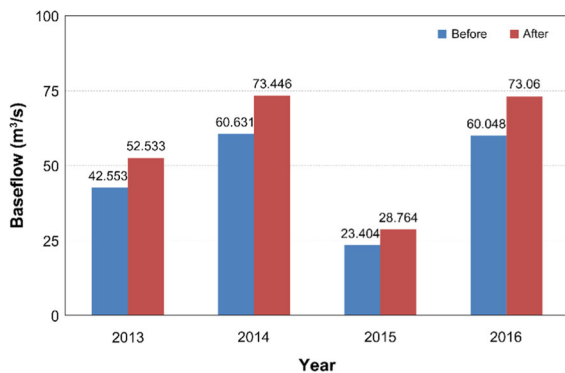


Figure 11

Graph of change in baseflow before and after calibration and validation

year. The average baseflow before calibration and validation was  $46.659 \text{ m}^3/\text{s}$ , and it was increased to  $56.951 \text{ m}^3/\text{s}$  after calibration and validation. Although there is a difference in baseflow depending on precipitation for each year, it was shown to

increase after calibration and validation in all the years, and in 2015, the overall baseflow is low due to the effects of precipitation. Figure 12 shows a comparison of precipitation in the study area with the baseflow runoff before and after calibration and validation. The change of baseflow is shown depending on season and precipitation. It was confirmed that the difference in baseflow occurred according to the improvement of calibration, validation, and accuracy.

## 6. Conclusions

The study area, Cheongsong Yongjeon stream basin, is a designated rural water management area for securing water resources through the utilization of baseflow and groundwater. Therefore, this study simulated the runoff and baseflow of this area using the SWAT model, which is widely used for hydrological analysis, and compared the results after calibration and validation. In addition, the study checked for any uncertainties in the data by using SWAT-CUP Premium.

- According to the SWAT analysis, the  $R^2$  value of simulated and observed flows was 0.40, indicating low accuracy. However, after calibration and validation using SWAT-CUP Premium during the same period, the  $R^2$  of simulated and observed flows increased to 0.71. In terms of the evaluation indexes, the NS was 0.51, PBIAS was 37.1, the P-factor was 0.73, and the R-factor was 0.33, showing an improved relationship between observed and simulated flows. In particular, the NS was greater than 0.50, indicating a significant improvement in uncertainty, and the P-factor for simulated runoff was also highly accurate.
- The baseflow before and after calibration and validation was also compared using surface water runoff, intermediate runoff, and groundwater runoff variables. The average baseflow before calibration and validation was  $46.659 \text{ m}^3/\text{s}$ , which increased to  $56.951 \text{ m}^3/\text{s}$  after calibration and validation. Although there are differences in baseflow depending on the season and precipitation level, it was able to obtain more accurate values than before calibration and validation. In

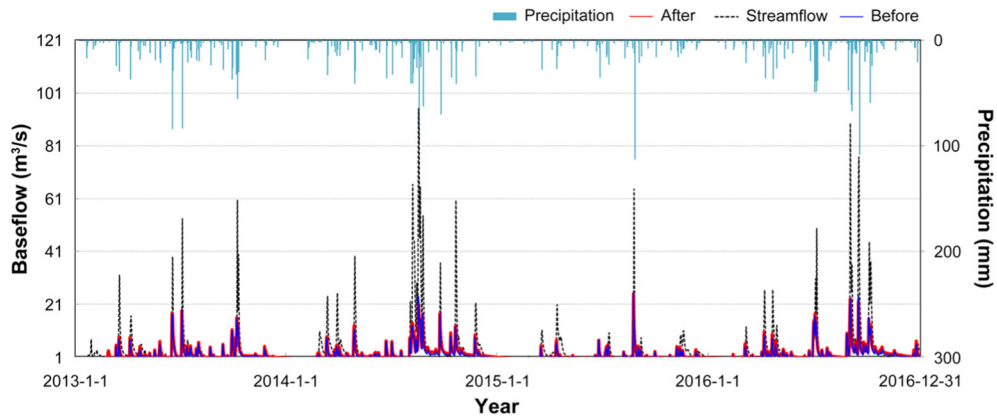


Figure 12

Graph of change in baseflow before and after calibration and validation compared to precipitation

particular, the use of SWAT-CUP Premium's SPE algorithm parameters is considered to be highly applicable for analyzing rainfall–runoff relationships and managing water resources in small rural areas.

- Baseflow is difficult to analyze because it changes depending on various environmental factors, such as climate and geological variables (e.g., geological faults). There are also limitations to estimating quantitative baseflow due to the uncertainty in baseflow analysis. However, integrated analysis that considers surface water and groundwater, calibration and validation using SWAT-CUP Premium, and uncertainty improvement enables more accurate baseflow calculations. The findings of this study can also be used as fundamental data for securing water resources through integrated surface water–groundwater analysis in rural areas that require water resource management, as in the case of the study area.
- However, this study has limitations when it comes to investigating natural baseflow due to the lack of measured baseflow data and limits when it comes to quantifying model input data. Therefore, data acquisition and research on river flow, direct runoff, and baseflow should be continued in order to more accurately identify river characteristics. Long-term baseflow observations on a national level are also necessary to evaluate the baseflow analysis accuracy of watershed models.

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### *Data Availability*

Data can be provided upon request.

### **Declarations**

**Conflict of interest** All authors declare that they have no conflict of interest.

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