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ARTICLE

Modification of SWAT auto-calibration for accurate flow estimation at all flow regimes

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Abstract To secure accuracy in the Soil and Water Assessment Tool (SWAT) simulation for various hydrology and water quality studies, calibration and validation should be performed. When calibrating and validating the SWAT model with measured data, the Nash–Sutcliffe efficiency (NSE) is widely used, and is also used as a goal function of auto-calibration in the current SWAT model (SWAT ver. 2009). However, the NSE value has been known to be influenced by high values within a given dataset, at the cost of the accuracy in estimated lower flow values. Furthermore, the NSE is unable to consider direct runoff and baseflow separately. In this study, the existing SWAT auto-calibration was modified with direct runoff separation and flow clustering calibration, and current and modified SWAT auto-calibration were applied to the Soyanggang-dam watershed in South Korea. As a result, the NSE values for total streamflow, high flow, and low flow groups in direct runoff, and baseflow estimated through modified SWAT auto-calibration were 0.84, 0.34, 0.09, and 0.90, respectively. The NSE values of current SWAT auto-calibration were 0.83, 0.47, −0.14, and 0.90, respectively. As shown in this study, the modified SWAT auto-calibration shows better calibration results than current SWAT auto-calibration. With these capabilities, the SWAT-estimated flow matched the measured flow data

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well for the entire flow regime. The modified SWAT auto-calibration module developed in this study will provide a very efficient tool for the accurate simulation of hydrology, sediment transport, and water quality with no additional input datasets.

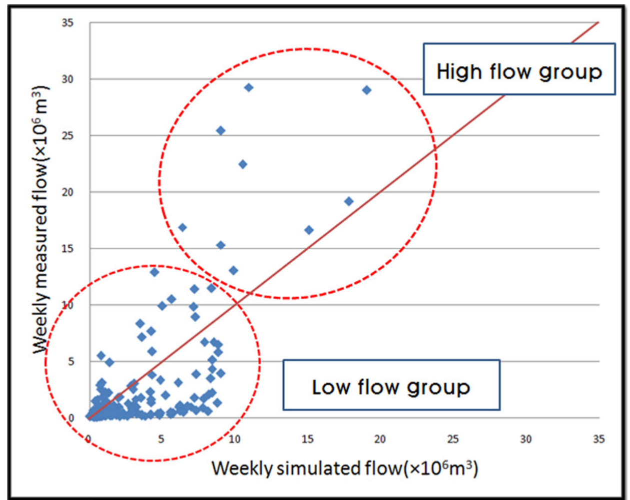
Keywords Nash–Sutcliffe efficiency · Auto-calibration · K-means clustering · Eckhardt digital filter

Introduction

Hydrologic models should be calibrated and validated when they are applied to a real watershed. Accordingly, several efficiency criteria have been used to evaluate the behavior and performance of hydrologic models. Among these efficiency criteria, the Nash and Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970) is often used to assess the predictive power of hydrological models. The NSE ranges from $-\infty$ to 1, where an efficiency of 1 corresponds to a perfect match of simulated and observed data.

The NSE has been widely used in calibration and validation for hydrological components (George et al. 2004; Lautenbach et al. 2009; Verbunt et al. 2005; Mitchell et al. 2001). The greater NSE value means that models reflect the hydrological behaviors well enough to simulate natural hydrological processes.

The Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998) is one of the models most typically used to predict hydrology and water quality in watersheds. In many SWAT application studies, the NSE has been frequently used to evaluate model performance (Park et al. 2007; Ndomba et al. 2008; Wu and Johnston 2007; Pisinaras et al. 2010). However, the NSE is known to be strongly influenced by high values in the dataset (Legates and McCabe 1999; McCuen et al. 2006). Park et al. (2007) compared SWAT-estimated weekly flow data with measured weekly flow data based on the NSE. The NSE for the total streamflow was 0.683, which indicated the simulated flow data match measured data (Donigian 2000). However, after clustering all flow data into flow group I and flow group II using the K-means clustering algorithm (MacQueen 1967), the NSE for flow group I (high flow) and flow group II (low flow) were low, and even became negative, implying that the average of measured data in flow group II (low flow) should be used instead of model-simulated value (Fig. 1). This result suggested that the use of NSE for flow evaluation in watersheds in summer monsoon climate areas, where the coefficient of river regime is usually greater due to torrential rainfall during summer, was not sufficient.



Total NSE	0.683
NSE for high flow group	-0.482
NSE for low flow group	0.058

Fig. 1 Comparison of NSE values for high flow, low flow, and total flow for showing the weakness of NSE value

Figure 1 indicates that if the NSE values for all flow groups are evaluated with higher accuracy, accurate SWAT total stream flow estimation could be obtained.

In the current SWAT model, the auto-calibration tool (Van Griensven et al. 2002) is used to automatically estimate the best input parameters for a given watershed. It has been widely used because it can reduce the calibration effort and save significant amounts of time (Van Griensven et al. 2002; Eckhardt and Arnold 2001; Van Griensven and Bauwens 2003). The SWAT auto-calibration uses the Parameter Solution (ParaSol) algorithm (Van Griensven and Meixner 2006). The goal function of ParaSol is the greatest NSE. This indicates that there are higher chances of a greater NSE value, although simulated data do not match measured data reasonable for all flow regimes. Also, the current SWAT auto-calibration has limitations in terms of calibrating direct runoff and all flow regimes, which means there could be errors in auto-calibration of SWAT simulation for direct runoff and baseflow separately. Therefore, calibration of high and low flow regimes separately is highly recommended.

Thus, the objectives of this study were to (1) modify SWAT auto-calibration with direct runoff separation and K-means clustering algorithm (MacQueen 1967) to calibrate high/low flow and baseflow separately and (2) to evaluate the modified SWAT auto-calibration module by comparing calibration results to the current SWAT auto-calibration module for a study watershed.

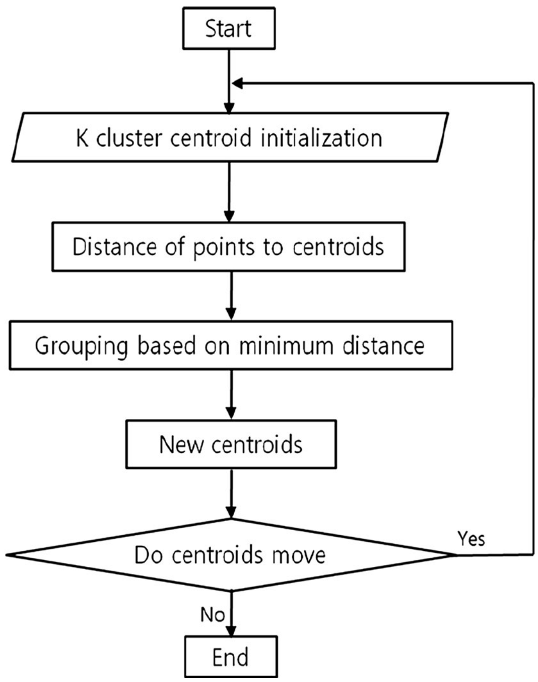


Fig. 2 Main steps of the K-means clustering algorithm (MacQueen 1967)

Previous research

Flow clustering calibration and direct runoff separation

In many hydrology studies, the NSE has been often utilized to evaluate model performance. However, the NSE has been known that it is affected by one big data among dataset. Thus, clustering method has been often utilized to group the data into multiple groups. The K-means clustering algorithm (MacQueen 1967) is one of the simplest unsupervised learning algorithms to solve the clustering problems. Among many clustering methods based on minimizing a formal objective function, it is one of the most widely used and studied methods (Lai and Huang 2010; Bandyopadhyay and Maulik 2002; Pandit et al. 2011).

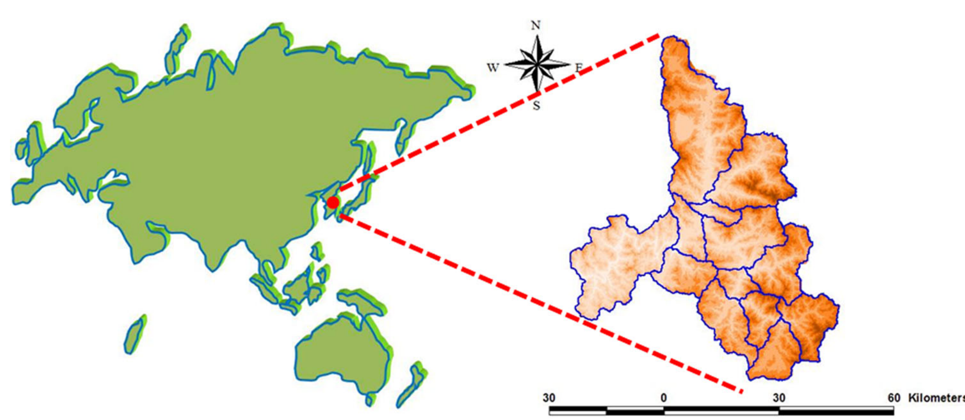
The main idea of K-means clustering is to define centroids using a given dataset. These centroids should be placed in an elaborate way because different coordinates cause different results (Zhou and Liu 2008). The first step of the K-means clustering algorithm is to decide on the centroid coordinate, and the second step is to decide on the distance of each object from the centroids. The third step is to group the objects based on the minimum distance. This process can be repeated until the K centroids do not move (Zhou and Liu 2008). Finally, this algorithm aims at minimizing an objective function (Eq. 1), in this case a squared error function,

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n_i} ||x_{ij} - z_i||^2, \tag{1}$$

where x_{ij} is the jth point in the ith cluster, z_i is the reference point of the ith cluster, and n_i is the number of points in that cluster. The notation $\|x_{ij} - z_i\|$ stands for the distance between x_{ij} and z_i. Hence, the error measure J indicates the overall spread of data points about their reference points. To achieve a representative clustering, J should be as small as possible. Figure 2 shows the main steps of the K-means clustering algorithm.

Total stream flow is composed of direct runoff and baseflow. Accordingly, SWAT-estimated total stream flow should be evaluated after the concurrent calibration of direct runoff and baseflow components. Many methods (i.e., master groundwater depletion curve method, straight line method, fixed base method, variable slope method, etc.) have been used to separate direct runoff and baseflow in watersheds (Chow et al. 1988; Rutledge 1993; Sloto and Crouse 1996). Among these methods, the Web-GIS-based Hydrograph Analysis Tool (WHAT; https://engineering.purdue.edu/~what) (Lim et al. 2005, 2010) has been widely used because of its easy-to-use web-based interface and advanced separation modules, such as the local

Fig. 3 Location of the Soyanggang-dam watershed



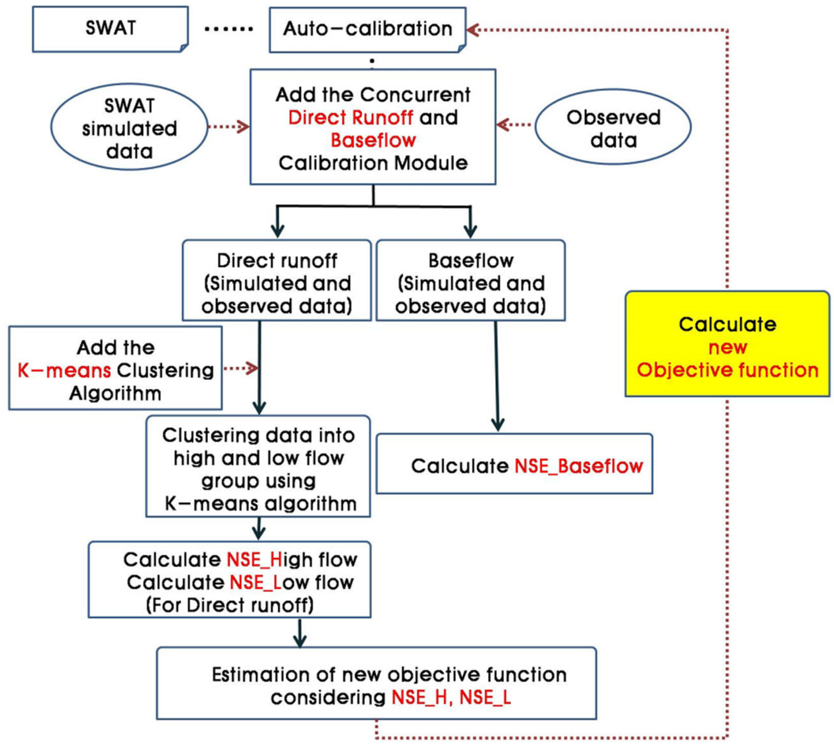


Fig. 4 Modification of SWAT auto-calibration using direct runoff separation and flow clustering calibration modules

minimum method, the BFLOW digital filter method, and the Eckhardt filter method (Eckhardt 2005).

Eckhardt (2005) proposed the general form of a digital filter considering filter parameter and $\mathrm{BFI}_{\max}$ (Eq. 2)

$$b_t = \frac{(1-\mathrm{BFI}_{\max}) \times \alpha \times b_{t-1} + (1-\alpha) \times \mathrm{BFI}_{\max} \times Q_t}{1-\alpha \times \mathrm{BFI}_{\max}}, \quad (2)$$

where b_t is the filtered baseflow at time step t; b_{t-1} is the filtered baseflow at the $t-1$ time step; $\mathrm{BFI}_{\max}$ is the maximum value of the long-term ratio of baseflow to total streamflow; α is the filter parameter, and Q_t is the total streamflow at the t time step (m^3/s). Eckhardt (2005) proposed the use of $\mathrm{BFI}_{\max}$ values of 0.80 for perennial streams with porous aquifers, 0.50 for ephemeral streams with porous aquifers, and 0.25 for perennial streams with hard rock aquifers. In this study, 0.80 is determined as the $\mathrm{BFI}_{\max}$ value, and the Eckhardt digital filter with $\mathrm{BFI}_{\max}$ value of 0.80 was used in SWAT auto-calibration to separate direct runoff and baseflow component from total stream flow for each run during auto-calibration processes.

Materials and methods

Study area

Soyanggang-dam watershed is located in Gangwon province in South Korea (Fig. 3). The basin area of Soyanggang-dam is about 2703 km^2, and it consists mainly of forest (89.6 %), agricultural area (5.3 %), urban (0.7 %), and bare ground (0.53 %). The average annual precipitation is 1200 mm, and the coefficients of river regime at this watershed are high because the Soyanggang-dam watershed is located in a typical monsoon climate area and intense precipitation takes place during the summer. The coefficient of river regime of the Han River in South Korea is over 300, which is much greater than those in other countries. The coefficient of river regime at Soyanggang-dam watershed was above 2000 in 2005. Average flow rates for the high flow regime at the study watershed was 303 m^3/s, and flow rate for the low flow regime was 1.2 m^3/s. Average elevation and slope are approximately 650.5 m and 40.6 %, respectively (Yoon et al. 2007).

Modification of auto-calibration using direct runoff separation and flow clustering calibration modules

Parameter Solution (Parasol) (Van Griensven and Meixner 2006) is one of the calibration methods in the SWAT auto-calibration module, and it is used to change the parameters automatically. The ParaSol is based on the shuffle complex (SCE-UA) algorithm, and it enables sensitivity analysis, calibration, validation, and uncertainty analysis of SWAT model automatically. However, current SWAT auto-calibration/ParaSol only uses total streamflow in flow auto-calibration procedures, although accuracies in high and low direct runoff and baseflow estimation should be secured separately. In this study, ParaSol was modified to calibrate SWAT model for high and low flow conditions and baseflow in the watersheds using Eckhardt digital filter and K-means clustering algorithm. Through the Eckhardt digital filter equation, direct runoff and baseflow are separated, and then direct runoff is clustered using K-means clustering algorithm to the low and high flow groups.

ParaSol uses the sum of squares of the residuals (SSQ) as an objective function and the NSE as a goal function to determine the best parameters. The NSE value is calculated as shown in Eq. 3, where O_i is observed flow, P_i is simulated flow, and $\bar{O}$ and $\bar{P}$ are the average values of observed and simulated flow, and the numerator of this equation is SSQ.

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}. \tag{3}$$

SWAT auto-calibration using direct runoff separation and flow clustering calibration modules was developed by replacing the objective function in Parasol with this new objective function. Figure 4 shows how the modified SWAT auto-calibration was modified. The first step was to divide total observed and simulated flow into direct runoff and baseflow using the Eckhardt digital filter equation (Eckhardt 2005). Second, direct runoff was separated into low and high flow groups using K-means clustering algorithm (MacQueen 1967). In this procedure, Eq. 1 is used to find the position of centroids using a given dataset, and then observed and simulated direct runoffs are divided into two groups based on position of centroids. Third, the NSE values and new objective function were calculated separately for each flow groups: NSE_baseflow, NSE_direct_High, and NSE_direct_Low. Finally, the objective function was replaced by new objective function.

Table 1 Twenty-six parameters used in the SWAT auto-calibration module

Parameter	Description	Variation method	Lower bound	Upper bound
ALPHA_BF	Baseflow alpha factor	Replace by value	0	1
BIOMIX	Biological mixing efficiency	Replace by value	0	1
BLAI	Maximum potential leaf area index	Replace by value	0	1
CANMX	Maximum canopy storage	Replace by value	0	10
CH_K2	Effective hydraulic conductivity in main channel alluvium	Replace by value	0	150
CH_N2	Mannings' *n* value for the main channel	Replace by value	0	1
CN2	SCS runoff curve number for moisture condition II	Multiply by value (%)	−25	25
EPCO	Plant evaporation compensation factor		0	1
ESCO	Soil evaporation compensation factor	Replace by value	0	1
GW_DELAY	Groundwater delay	Add to value	−10	10
GW_REVAP	Groundwater "revap" coefficient	Add to value	−0.036	0.036
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	Add to value	−1000	1000
REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	Add to value	−100	100
SFTMP	Snow melt base temperature (°C)	Replace by value	0	5
SLOPE	Increase the lateral flow	Multiply by value (%)	−25	25
SLSUBBSN	Average slope length	Multiply by value (%)	−25	25
SMFMN	Minimum melt rate for snow (mm/°C/day)	Replace by value	0	10
SMFMX	Maximum melt rate for snow (mm/°C/day)	Replace by value	0	10
SMTMP	Snow melt base temperature (°C)	Multiply by value (%)	−25	25
SOL_AlB	Moist soil albedo	Multiply by value (%)	−25	25
SOL_AWC	Available water capacity of the soil layer	Multiply by value (%)	−25	25
SOL_K	Saturated hydraulic conductivity (mm/h)	Multiply by value (%)	−25	25
SOL_Z	Soil depth (%)	Multiply by value (%)	−25	25
SURLAG	Surface runoff lag time	Replace by value	0	10
TIMP	Snow pack temperature lag factor	Replace by value	0	1
TLAPS	Temperature laps rate (°C/km)	Replace by value	0	50

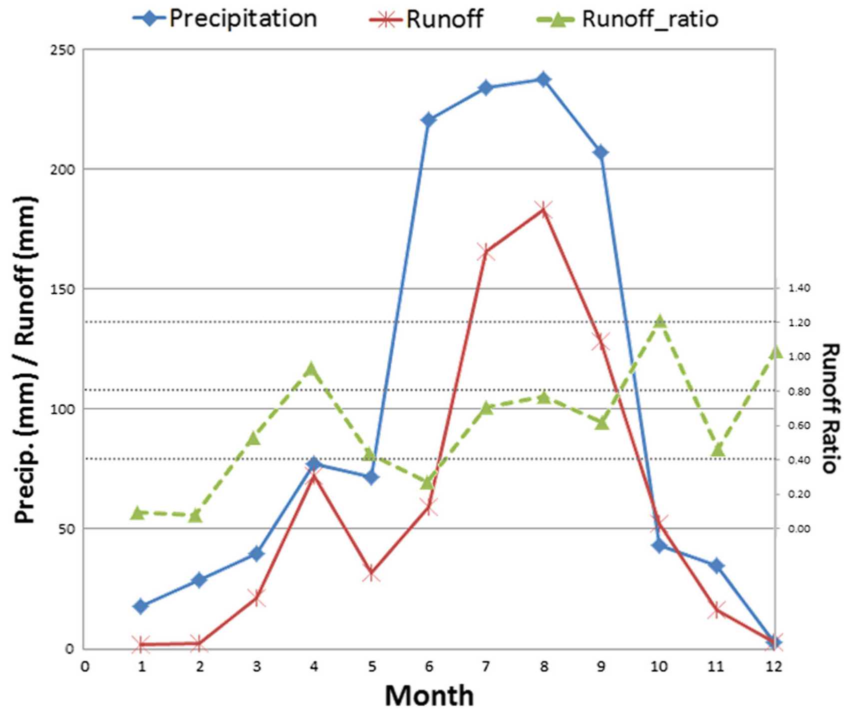


Fig. 5 Monthly precipitation, runoff, and runoff ratio in the study area

Application of modified auto-calibration modules

The modified auto-calibration was applied to the study watershed to evaluate the effects of the improved module in flow estimation. In the SWAT auto-calibration, there are twenty-six parameters to be calibrated for fitting simulated to observed streamflow (Table 1). In the SWAT auto-calibration module, three variation methods are available to replace the parameter automatically for each simulation. "Replace by value" replaces the initial parameter by new value in selected hydrological response unit (HRU); "Add to value" adds the value to initial parameter in the selected HRU; and "Multiply by value" multiplies the initial parameter by a value in the selected HRU. During the auto-calibration procedure, all parameters were substituted within the range between their lower and upper bounds (Winchell et al. 2010). In this study, these three variation methods were used in evaluating the current and modified SWAT auto-calibration runs.

The current SWAT auto-calibration and the modified SWAT auto-calibration modules using direct runoff separation and flow clustering calibration modules were applied to determine the best parameters for the study watershed using the same datasets and compared based on the NSE values for direct runoff and baseflow. The modified SWAT auto-calibration can be used without any change/modification in ArcSWAT interface, since the same file structures are used in calibration processes. Various objective functions could be utilized depending on flow status at the study watershed. In this study, the coefficient of determination (Eq. 4) and index of agreement d (Eq. 5) were used to evaluate current and modified SWAT auto-calibration modules.

$$R^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n} (P_i - \bar{P})^2}} \right)^2 \quad (4)$$

$$d = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (|P_i - \bar{O}| + |O_i - \bar{O}|)^2}, \quad (5)$$

where O_i is observed flow, P_i is simulated flow, and $\bar{O}$ and $\bar{P}$ are the average values of observed and simulated flow, respectively.

Results and discussion

In a Soyanggang-dam watershed, there are eleven rainfall observatories; Fig. 5 shows that average monthly precipitation, runoff, and runoff ratio in study area; the average precipitation in 2005 was 1216 mm. As shown in Fig. 5, a significant amount of rainfall occurred during the summer; 57 % of precipitation occurred in June, July, and August. This is very common in most of the watersheds in Korea, under typical monsoon climate area.

The best parameters determined based on the current and modified SWAT auto-calibration runs are listed in

Table 2 Comparison of best parameters of current and modified auto-calibration modules

Parameter	Current auto-calibration	Auto-calibration modified by direct runoff separation and flow clustering calibration module
ALPHA_BF	0.91	0.98
BIOMIX	0.84	0.78
BLAI	0.26	0.48
CANMX	8.27	0.82
CH_K2	86.98	140.63
CH_N2	0.67	0.39
CN2	−22.67 (%)	−4.89 (%)
EPCO	0.08	0.84
ESCO	0.94	0.69
GW_DELAY	−5.12	+5.74
GW_REVAP	−0.03	0.00
GWQMN	+581.60	+592.31
REVAPMN	−89.08	−72.35
SFTMP	4.65	1.10
SLOPE	−13.29 (%)	−24.51 (%)
SLSUBBSN	−19.57 (%)	−14.88 (%)
SMFMN	7.78	0.69
SMFMX	6.71	3.19
SMTMP	14.69 (%)	−7.16 (%)
SOL_AlB	−15.81 (%)	20.38 (%)
SOL_AWC	5.98 (%)	13.31 (%)
SOL_K	0.15 (%)	23.59 (%)
SOL_Z	13.89 (%)	−16.75 (%)
SURLAG	8.84	2.07
TIMP	0.17	0.37
TLAPS	18.50	44.84

Table 2. With more than 10,000 runs, these two auto-calibration programs identified the best parameters within the upper and low bounds of each parameter. The value in Table 2 indicates that the goal function in the auto-calibration module plays an important role in determining best parameters. The value for the NRCS runoff curve number for moisture condition II (CN2) is known as one of the most sensitive SWAT parameters when simulating direct runoff (Lenhart et al. 2002). The best CN2 value from current SWAT auto-calibration was −22.67 % ("Multiply by value" variation method) and −4.89 % with the modified SWAT auto-calibration module. The CN2 estimated with the modified SWAT auto-calibration module was closer to the initial default parameter values, indicating these CN2 values are acceptable compared with the CN2 values with the current SWAT auto-calibration modules.

Table 3 shows the NSE values for total streamflow, high and low flow groups of direct runoff, and baseflow. The NSE values for high and low flow groups of direct runoff were 0.47 and −0.14 when using the current SWAT auto-calibration module, and the NSE values for the two flow groups using the modified SWAT auto-calibration module were 0.34 and 0.09. The NSE values for baseflow component were 0.90 for both auto-calibration modules. According to the Nash and Sutcliffe (1970), if the NSE is less than zero, the mean value of the observation would be a better predictor than the model-estimated value. The NSE value for total streamflow using the current SWAT auto-calibration module was 0.83, and 0.84 when using the modified SWAT auto-calibration module (Fig. 6). These results indicate that the SWAT-simulated results with the current SWAT auto-calibration module could result in errors in simulated direct runoff, especially for the low flow group (NSE value of −0.14) of direct runoff, although the NSE values for total streamflow are acceptable (>0.83). If the NSE values for high and low flow groups of direct runoff and baseflow are all positive, the higher NSE values for the total streamflow should be expected as shown in this study. As shown in Fig. 7, modified SWAT auto-calibration gave better result (+NSE value), compared with that (−NSE value) from current SWAT auto-calibration.

The coefficient of determination for low flow improved from 0.35 (current SWAT auto-calibration) to 0.41 (modified SWAT auto-calibration). Also, the coefficient of determination for Baseflow increased slightly as shown in Table 4. When the index of agreement d was used, the similar observation was found (Table 5).

Summary and conclusion

The SWAT auto-calibration module was modified using direct runoff separation and flow clustering calibration. The modified SWAT auto-calibration module was applied and

Table 3 Comparison of the NSE values of current and modified auto-calibration modules

	NSE-streamflow	NSE-direct runoff		NSE-baseflow
		NSE-high flow	NSE-low flow	
Current auto-calibration	0.83	0.47 (+)	−0.14 (−)	0.90 (+)
Auto-calibration modified by direct runoff separation and flow clustering calibration module	0.84	0.34 (+)	0.09 (+)	0.90 (+)

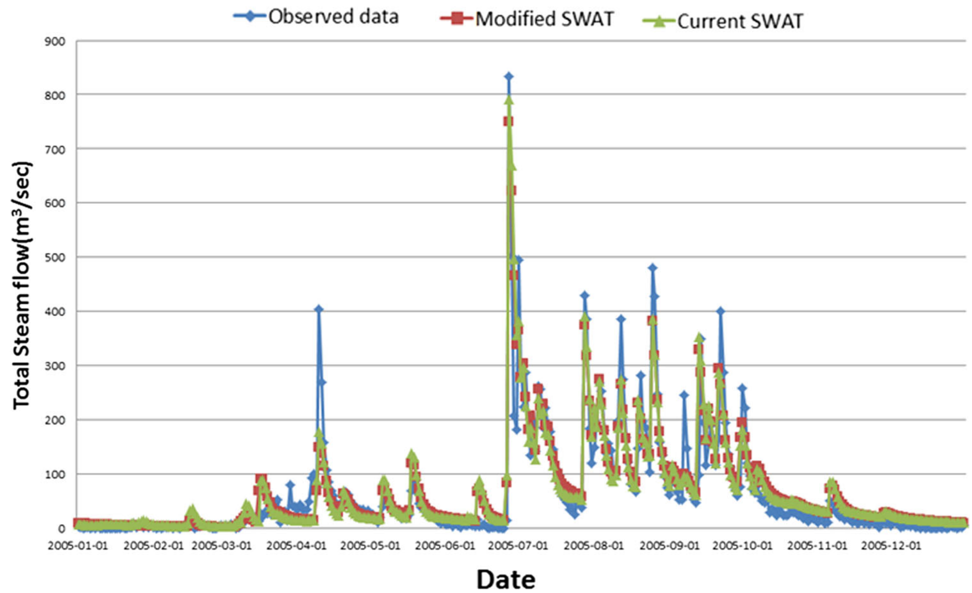
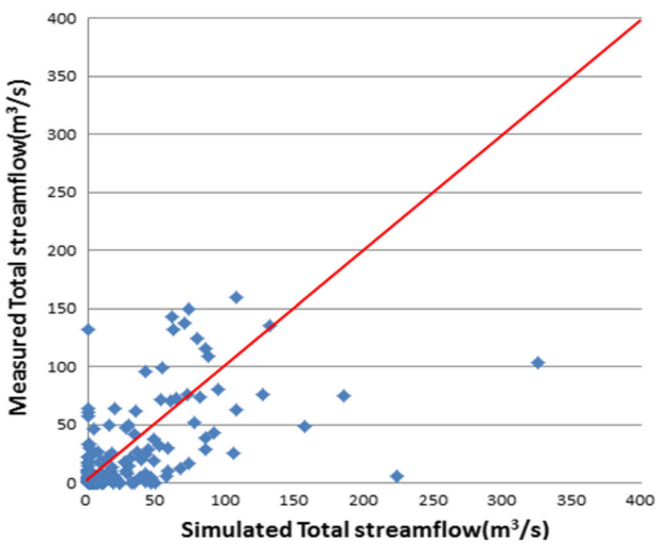
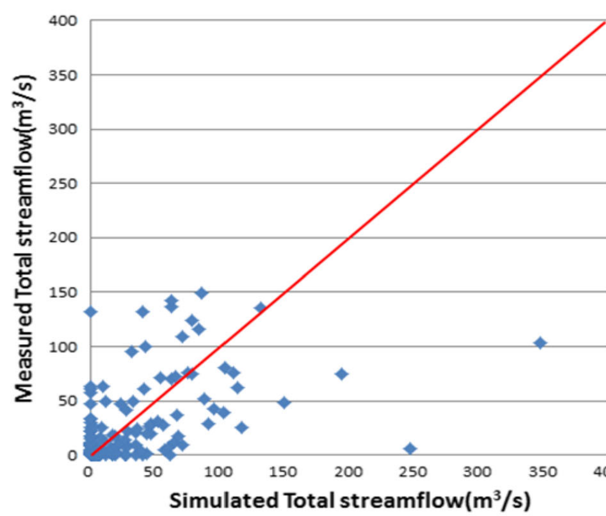


Fig. 6 Comparison of stream flows of current and modified auto-calibration



(a) Modified SWAT auto-calibration



(b) Current SWAT auto-calibration

Fig. 7 Comparison of low flows of current and modified auto-calibration

Table 4 Comparison of the R^2 values of current and modified auto-calibration modules

	R^2-streamflow	R^2-direct runoff		R^2-baseflow
		R^2-high flow	R^2-low flow	
Current auto-calibration	0.84	0.81	0.35	0.92
Auto-calibration modified by direct runoff separation and flow clustering calibration module	0.84	0.81	0.41	0.93

compared with the current auto-calibration module to evaluate the performance of the modified module. High and low flow groups of direct runoff and baseflow should be calibrated with positive NSE values to secure higher accuracies of SWAT estimation in all flow regimes. Although the modified SWAT auto-calibration module did not provides better NSE values than that of the current SWAT auto-calibration, the calibration approaches used in

Table 5 Comparison of the index of agreement *d* values of current and modified auto-calibration modules

	d-streamflow	*d*-direct runoff		*d*-baseflow
		d-high flow	*d*-low flow	
Current auto-calibration	0.84	0.81	0.35	0.92
Auto-calibration modified by direct runoff separation and flow clustering calibration module	0.84	0.81	0.41	0.93

this study are more hydrologically appropriate for the watershed flow modeling, since high and low flow groups of direct runoff and baseflow are considered separately in the process.

In addition, the objective of this study was to develop better auto-calibration module for all flow regimes including high and low flow regimes, and all NSE values with modified SWAT auto-calibration were above 0. According to the study by Nash and Sutcliffe (1970), if the NSE value is 0 or below, the mean value of the observation would be a better predictor than the model-estimated value. But, the NSE value for low flow group of direct runoff with the current SWAT auto-calibration is below 0. It means the modified SWAT auto-calibration could estimate flow rate for all flow regimes. In addition, the modified SWAT auto-calibration provides better coefficient of determination and index of agreement d for low flow regime. This indicated that the modified SWAT auto-calibration should be used in evaluating hydrology and water quality during low flow period. In Korea, 10-year average low flow data are used to evaluate the total maximum daily load (TMDL), and the results obtained in this study could be utilized to estimate low flow rate at ungaged watershed after application of modified SWAT auto-calibration to a watershed covering ungaged watershed.

In the modified SWAT auto-calibration module, the NSE is used as a goal function. However, there are many metrics to evaluate calibration. Thus, other metrics such as index of agreement *d*, root mean square error (RMSE), modified NSE, modified *d*, and relative NSE and *d* could be evaluated with modifications in the goal function, since some of these metrics may be less influenced by higher values in the flow dataset. In addition, the modified SWAT auto-calibration module should be evaluated for watersheds with different precipitation patterns and amounts to guarantee its efficiency in SWAT flow calibrations.

Accurate estimation of flow at various flow regimes is very important in accurate modeling of soil erosion and pollutant loads at stream and watersheds. Therefore, the results of this study could give the preferable method for calibrating hydrologic component and estimation of water quality.

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