An interactive graphical interface tool for parameter calibration, sensitivity analysis, uncertainty analysis, and visualization for the Soil and Water Assessment Tool

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Abstract

The Soil and Water Assessment Tool (SWAT) is one of the most widely used and well-tested eco-hydrological models. However, parameter calibration, sensitivity analysis and uncertainty analysis remain among the most challenging tasks. Existing SWAT parameter calibration, sensitivity analysis, and uncertainty analysis tools are either commercial products or free tools with limited options. This study demonstrates an interactive graphical user interface tool in the R environment for SWAT parameter calibration, sensitivity and uncertainty analyses, and visualization, called *R-SWAT*. Different R functions/packages for parameter calibration, sensitivity analysis, and uncertainty analysis have been incorporated into *R-SWAT*. Third-party packages can be integrated into *R-SWAT* with minimum effort. The application of *R-SWAT* for a test case study demonstrates its functionalities. In general, *R-SWAT* (1) is a potential platform for developing and testing new sensitivity or optimization packages, and (2) promotes the understanding of hydrological processes with open-source SWAT and R.

Keywords: graphical user interface, model calibration, parameter sensitivity, uncertainty analysis, R, SWAT model

Software availability

- Name of software: *R-SWAT* (version v1.0.0)
- Developer and contact address: Tam V. Nguyen (tam.nguyen@ufz.de), Department of Hydrogeology, Helmholtz Centre for Environmental Research - UFZ, 04318 Leipzig, Germany.
- Year available: 2021
- Programming language: R
- Availability and cost: the source code, including links to tutorial videos and discussion group, is freely available at https://github.com/tamnva/R-SWAT.

1. Introduction

Hydrological model are a simplified representation of real-world physical processes (e.g., evapotranspiration, surface and subsurface flows, soil biogeochemical processes among others). Hydrological models assist scientists and engineers in managing water resources. In the last few decades, various models simulating different physical processes and levels of spatial detail have been developed, ranging from lumped conceptual models to physically-based distributed models. Some examples of these models are the Génie Rural à 4 paramètres Journalier (GRJ4, Perrin et al., 2003), the Soil and Water Assessment Tool (SWAT, Arnold et al., 1998; Arnold, Kiniry, et al., 2012), the HYdrological Predictions for the Environment model (HYPE, Lindström et al., 2010), the mesoscale Hydrologic Model (mHM, Samaniego et al., 2010), and HydroGeoSphere (HGS, Therrien et al., 2010). Hydrological models often have to be calibrated using a set of effective parameters (Skaggs et al., 2012) to make sure that the models can represent the process of interest.

SWAT is one of the most widely used hydrological models, and it is the most used water quality model (Fu et al., 2019). SWAT has been applied to evaluate the impact of land use management practices on water, sediments, and nutrient yields at the catchment scale (Arnold et al., 1998; Arnold, Kiniry, et al., 2012). SWAT has been tested at various catchments worldwide (Arnold, Moriasi, et al., 2012). The number of published studies related to SWAT has increased drastically, with more than 5000 papers to date (https://www.card.iastate.edu/swat_articles/, accessed 10 March 2022). Besides the technical merit of the conceptual model of SWAT, five main reasons explain the success of SWAT: (1) technical support via different platforms, (2) accessibility to model input data at the global scale, (3) user-friendly GIS-based graphical user interface (GUI) for model processing (e.g., ArcSWAT and QSWAT), (4) free, open-source code with different community tools for input data preparation and post-processing (a list of these tools can be found at https://swat.tamu.edu/, accessed 10 March 2022), and (5) a well-connected worldwide user community.

One of the challenges when working with SWAT is to perform parameter calibration, sensitivity analysis, and uncertainty analysis. This is due to not only the complex SWAT model structure but also the high technical effort required to modify the parameter values in SWAT. There could be up to thousands of SWAT parameters located in different files (in ASCII format) (Neitsch et al., 2011). To help SWAT users perform parameter calibration, sensitivity analysis, and uncertainty analysis, SWAT-CUP (Abbaspour, 2015) was introduced. However, SWAT-CUP is a commercial software, and its free version is available for SWAT users with some restrictions, e.g., on the maximum number of simulations and on the parallel simulation options. The source code of SWAT-CUP is not available, so users cannot adapt the tool to their specific needs. For example, they cannot use objective functions or extract model outputs that are not defined in SWAT-CUP. In addition to SWAT-CUP, ArcSWAT and SWATEditor (https://swat.tamu.edu/software/, accessed 10 March 2022) also offer options for running SWAT with a given list of modified parameter values. However, they do not contain any technique for automatic parameter calibration, sensitivity analysis, and uncertainty analysis. In contrast, several free or open-source tools have been developed for either automatic or manual calibration, parameter sensitivity, and uncertainty analysis with SWAT+ (Bieger et al., 2017) which is a completely restructured version of SWAT. Two examples of these tools are the SWAT+ toolbox (Chawanda, 2021) and the Integrated Parameter Estimation and Uncertainty Analysis Tool Plus (IPEAT+, Yen et al., 2019). Developing such tools for SWAT is necessary, considering the wide use of SWAT.

In recent years, R (R Core Team, 2019) has emerged as a potential platform for developing open-source packages for hydrological research (Slater et al., 2019). Various R packages exist for parameter calibration, sensitivity analysis, uncertainty analysis (e.g., Husmann et al., 2017; Iooss et al., 2021; Zambrano-Bigiarini & Rojas, 2020), and parallelization (e.g., Microsoft Corporation & Weston, 2020; R Core Team, 2019). In the field of hydrological science, the R community is growing and now includes numerous packages for hydrological research (https://cran.r-project.org/web/views/Hydrology.html, accessed 10 March 2022). In addition, different packages for visualization and creating GUI are available in R, such as *ggplot2* (Wickham, 2011), *plotly* (Chang et al., 2021), and *shiny* packages (Chang et al., 2021), which facilitate visual evaluation of model outputs. The main advantage of R is that all packages are open-source and free for the community. Therefore, it would be beneficial to have a tool that connects SWAT with R.

Several R packages or scripts were developed for SWAT. The *SWATplusR* package (Schürz, 2019) was introduced for performing SWAT and SWAT+ simulations with provided parameters and returning model outputs. *SWATplusR* is well-documented with a workflow and illustrative examples (e.g., model calibration, parameter sensitivity analysis, and uncertainty analysis). Guillaume and Andrews (2012) developed R scripts for SWAT parameter uncertainty analysis with the *dream* (DiffeRential Evolution Adaptive Metropolis) package (Hartig et al., 2019). The *SWATmodel* package was created for running different SWAT versions (SWAT2005, SWAT2009; and SWAT2012) on different operating systems and processor platforms with given parameter values (Fuka et al., 2014). One of the advantages of these tools is that they are open-source, so users can further modify the source code for certain purposes. However, this requires a certain R knowledge level as well as knowledge of the provided source code. Therefore, having a GUI in addition to the open-source code and various ready-to-use techniques for parameter calibration, sensitivity analysis uncertainty analysis, and visualization of the model outputs would benefit SWAT users of different levels (beginners and experienced R users). This will promote hydrological research using SWAT and R, reduce the technical barrier between SWAT and R, thus promoting hydrological research using SWAT and R.

This paper introduces a new free and open-source R-based tool (called *R-SWAT*) with an interactive graphical user interface for SWAT parameter calibration, sensitivity analysis, uncertainty analysis, and visualization of the SWAT outputs. The proposed tool can be adapted to other models, e.g., SWAT+ (Bieger et al., 2017), HYPE (Lindström et al., 2010), or mHM (Samaniego et al., 2010). Here, SWAT was chosen as an example rather than the only possible hydrological model to couple with R.

2. Structure and functionalities of *R-SWAT*

To use *R-SWAT*, all SWAT input files in the *TxtInOut* folder must be created beforehand by external programs (e.g., ArcSWAT or QSWAT). *R-SWAT* provides functions for 1) updating SWAT input files, 2) parameter sensitivity analysis, 3) calibration and uncertainty analysis, 4) parallelization, 5) model output extraction and model performance evaluation, and 6) visualization of the model results (Figure 1). Details of these functions are described in the subsequent sections.

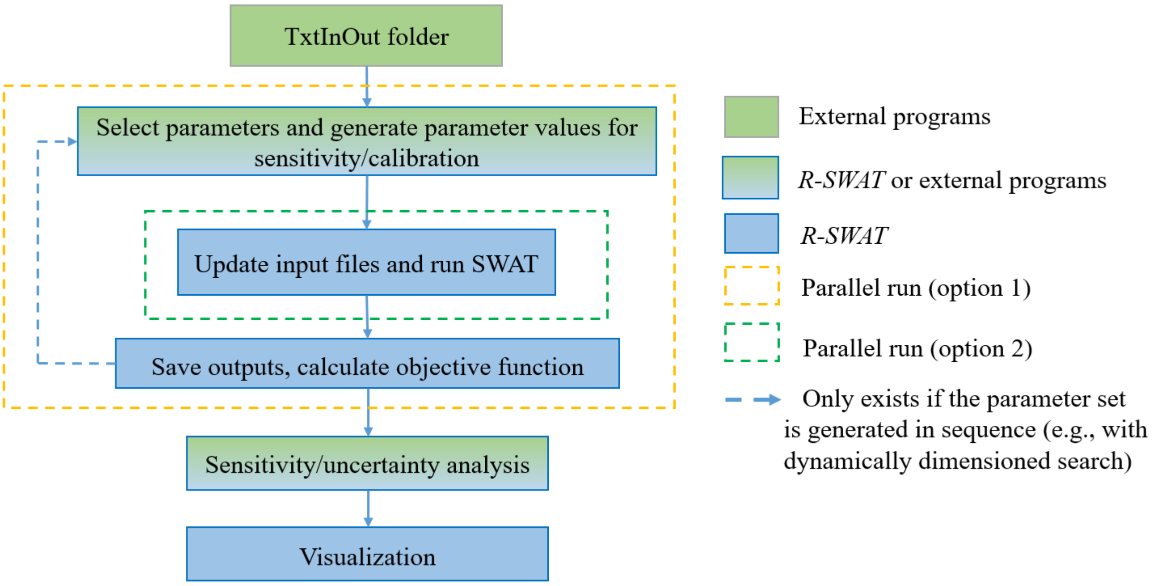

Figure 1. Overview of the structure and functionalities of *R-SWAT*.

2.1. Updating SWAT parameters

The number of SWAT parameters could be up to a thousand or more depending on the modeling area and the model setup. This is because SWAT can be implemented as a distributed model with parameters that are defined at different spatial levels (e.g., hydrological response unit - HRU, subbasin, and basin). To modify SWAT parameter values, knowledge of the input file and model structure is required. SWAT inputs are in the ASCII file format with various file extensions (e.g., ".hru", ".sub", and ".bsn"), representing different spatial modelling units and/or processes. Each file includes different parameters located in different lines with different number formats. In addition, new input files and new parameters can be introduced as SWAT is constantly being developed for specific purposes (e.g., Nguyen et al., 2020; Nguyen & Dietrich, 2018). Therefore, this study developed a general approach that allows modification of any parameter defined via the text file "*swatParam.txt*" (please see the supporting material *R-SWAT.pdf*). This facilitates the use of *R-SWAT* with any given SWAT version without reading/modifying the *R-SWAT* source code.

R-SWAT modifies multiple parameters in a single file and saves the file only once instead of in sequence (e.g., rewriting the same input file multiple times, modifying only one parameter each time) to reduce the writing time. Similar to SWAT-CUP (Abbaspour, 2014), *R-SWAT* uses three methods, relative change (Equation 1), absolute change (Equation 2), and replace (Equation 3) for modifying SWAT parameters (Figure 2):

$$p_{new} = p_{original} \cdot (1 + x) \quad (1)$$

$$p_{new} = p_{original} + x \quad (2)$$

$$p_{new} = x \quad (3)$$

where p_{new} is the modified parameter value, $p_{original}$ is the original parameter value created during the model setup, and x is the modified factor/value.

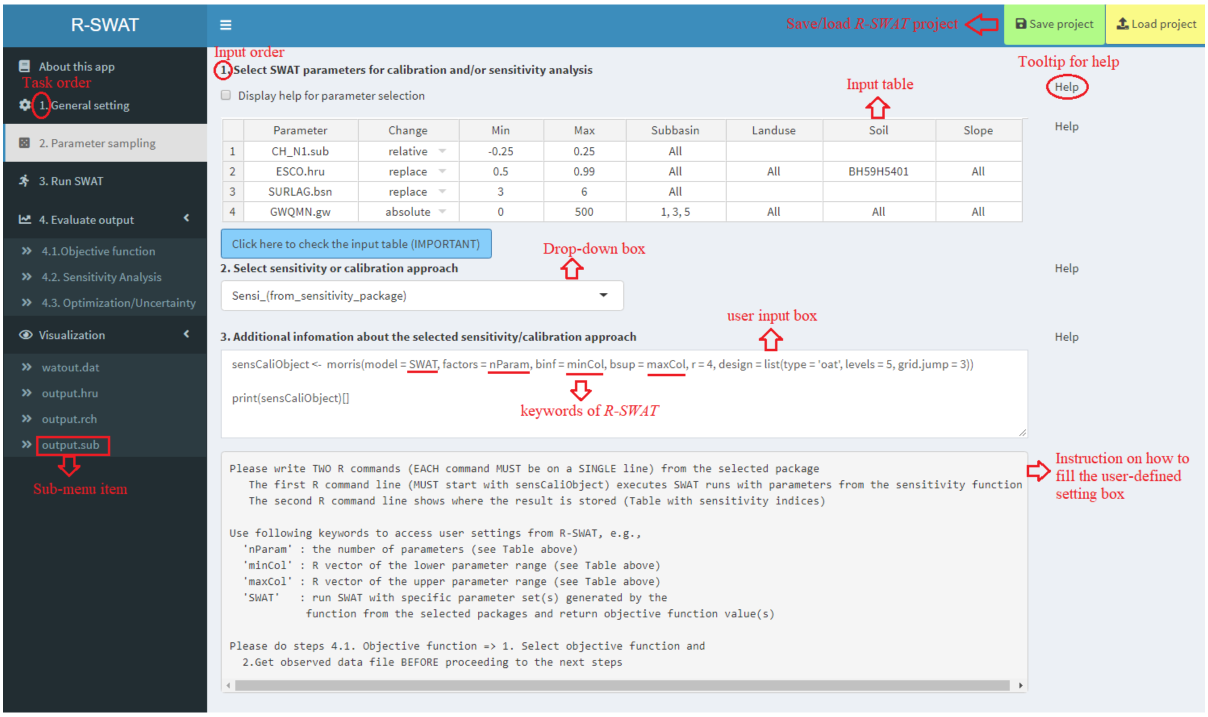

Figure 2. *R-SWAT* user interface for selecting parameters for sensitivity analysis or calibration (menu item “2. Parameter sampling”). Numbers in the left and right panels indicate the order of these tasks (unless a message states that a specific task needs to be done before).

2.2. Parameter sensitivity analysis

The current *R-SWAT* version uses the *sensitivity* R package (Iooss et al., 2021), which provides different functions for factor screening, and global sensitivity analysis with robustness analysis. Users need to type R functions from the *sensitivity* package in the user input box of *R-SWAT* (Figure 2). To couple *R-SWAT* with the *sensitivity* package, we use keywords to pass functions and variables from *R-SWAT* to functions of the *sensitivity* package (user input box, Figure 2). For example, (1) *SWAT* is the function that takes parameter values as inputs (all user settings from the *R-SWAT* interface were also passed to the *SWAT* function) and returns objective function values, (2) *minCol* and (3) *maxCol* are the vectors of minimum, and maximum ranges of the selected parameters respectively, and (4) *nParam* is the number of selected parameters (Figure 2). This option allows *R-SWAT* to use different functions of the *sensitivity* packages. Examples of the available sensitivity approaches in the *sensitivity* package are given in Table 1, while a complete list is given by Iooss et al. (2021). Integrating new sensitivity packages into *R-SWAT* only requires changing a single line in the *R-SWAT* code (as documented in the supporting material *R-SWAT.pdf*). Given the large number of parameters and the model runtime of SWAT, computationally cheaper methods, such as multiple start perturbation methods including the Morris (1991) and DELSA methods (Rakovec et al., 2014), are often preferred (Nossent et al., 2011). However, a much larger range of methods could be envisaged to examine the sensitivities of SWAT. For instance, previous studies have showed that the application of computationally expensive methods, such as the Sobol' (1993) method, can also be feasible, depending on the purpose of sensitivity analysis (Nossent et al., 2011; Sarrazin et al., 2016). The choice of the sensitivity analysis approach is beyond the scope of this study. We refer to Pianosi et al. (2016) for a review of the different available methods and their computational cost.

Table 1. Examples of available sensitivity functions in R-SWAT. Examples of input codes for the user-defined setting box (Figure 2) can be found in the supporting material (*R-SWAT.pdf*).

Sensitivity approach	Function/package	Reference
Morris's "OAT" elementary effects screening method	*morris/sensitivity*	Campolongo et al. (2007); Morris (1991); Pujol (2009)
Derivative-based Global Sensitivity Measures	*delsa/sensitivity*	Rakovec et al. (2014)
Variance-based sensitivity indices (Sobol' indices) for independent inputs	*sobol/sensitivity,* *fast99/sensitivity*	Sobol' (1993); Saltelli et al. (1999)
Multivariate linear regression	*R-SWAT*	Abbaspour (2014)

In addition, the global sensitivity analysis method using multivariate linear regression with parameters generated from uniform Latin Hypercube Sampling (e.g., Sequential Uncertainty FItting algorithm - SUFI-2, Abbaspour et al., 2004) was also added to *R-SWAT*. Furthermore, *R-SWAT* provides an option for running SWAT with parameter sets generated by other sensitivity analysis tools (by changing the option in the drop-down box, Figure 2). Then, *R-SWAT* returns the objective function values or the simulated values of the selected variables (Section 2.5) for further analysis. This allows *R-SWAT* to be coupled with other sensitivity analysis toolboxes that were written either in R or in other programming languages, e.g., the Sensitivity Analysis For Everybody (SAFE, Pianosi et al., 2015).

2.3. Parameter calibration or optimization

Parameter calibration is a process of adjusting model parameter values within their plausible ranges to minimize the differences between simulated and observed values. There exist various methods for parameter calibration (Arsenault et al., 2014), and many of them have been implemented as R packages (Husmann et al., 2017; Mullen, 2014; Zambrano-Bigiarini & Rojas, 2020). *R-SWAT* uses the *hydroPSO* (Zambrano-Bigiarini & Rojas, 2020), *optimization* (Husmann et al., 2017), and *nloptr* (Ypma et al., 2020) packages, which were designed for the optimization of complex loss functions. Some examples of the calibration/optimization approach with *R-SWAT* are in Table 2. Integrating new optimization packages into *R-SWAT* only requires changing a single line in the *R-SWAT* code (as documented in the supporting material *R-SWAT.pdf*)

Table 2. Some of available calibration/optimization approaches in *R-SWAT*. A complete list of optimization functions that can be used in *R-SWAT* is included in the *nloptr* package. Some examples of the input codes (Figure 2) can be found in the supporting material (*R-SWAT.pdf*).

Calibration/optimization approach	Function/package	Reference
Particle Swarm Optimisation (PSO)	*hydroPSO/hydroPSO*	Zambrano-Bigiarini & Rojas (2020)
Simulated Annealing (SA)	*optim_sa/optimization*	Husmann et al. (2017)
Bound Optimization by Quadratic Approximation (BOBYQA)	*bobyqa/nloptr*	Powell (2009)
Sequential Uncertainty Fitting (SUFI-2)	*R-SWAT*	Abbaspour et al. (2004)
Dynamically Dimensioned Search algorithm (DDS)	*R-SWAT*	Tolson & Shoemaker (2007)
Generalized Likelihood Uncertainty Estimation (GLUE)	*R-SWAT*	Beven & Binley (1992)

In addition, a similar approach to SUFI-2 (Abbaspour et al., 2004) and the Dynamically Dimensioned Search algorithm (DDS, Tolson & Shoemaker, 2007) was included (Table 2). SUFI-2 is often used for SWAT calibration and uncertainty analysis (Abbaspour et al., 2017; Arnold, Moriasi, et al., 2012). The DDS approach has been proven to be more efficient than others (Arsenault et al., 2014). A detailed description of the SUFI-2 and DDS approaches was presented elsewhere (Abbaspour, 2014; Tolson & Shoemaker, 2007) and different optimization approaches have also been covered in other publications (Arsenault et al., 2014; Khoi & Thom, 2015; Wu & Chen, 2015). Users could run SWAT with specific parameter sets (e.g., for manual calibration, local sensitivity analysis, or re-run the model with the optimal parameter set) from an external file (please see the supporting material *R-SWAT.pdf*).

2.4. Parallelization

R-SWAT executes SWAT in parallel to make use of available multi-core processors to save the user time (Figure 3). Parallel execution of SWAT is applied for the whole SWAT model instead of HRU- or subbasin-level processing (e.g., Zhang et al., 2021) because the latter option would require modification of the SWAT source code (this is not the scope of this study). If all parameter sets are known at the beginning (e.g., the Latin Hypercube Sampling (LHS) approach for parameter sensitivity and calibration), the number of models run on each core is determined by the number of parameter sets divided by the number of cores (e.g., SWAT-CUP, Abbaspour, 2014). If the number of model runs is not a multiplier of the number of cores, the remaining number of model runs is assigned to the last core. In case the parameter sets are generated in sequence (e.g., in the DDS optimization approach), the next parameter set is only generated if the model run is completed and evaluated with the previous parameter set and different parallelization options are proposed (Figure 4) as described below:

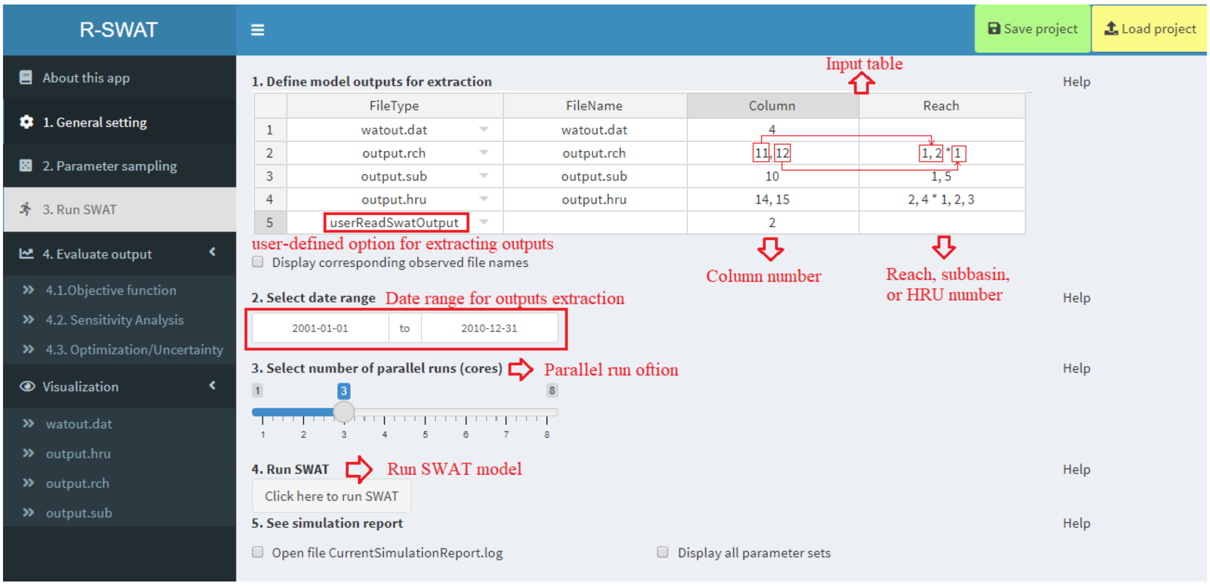

Figure 3. *R-SWAT* interface for model output extraction and parallel execution.

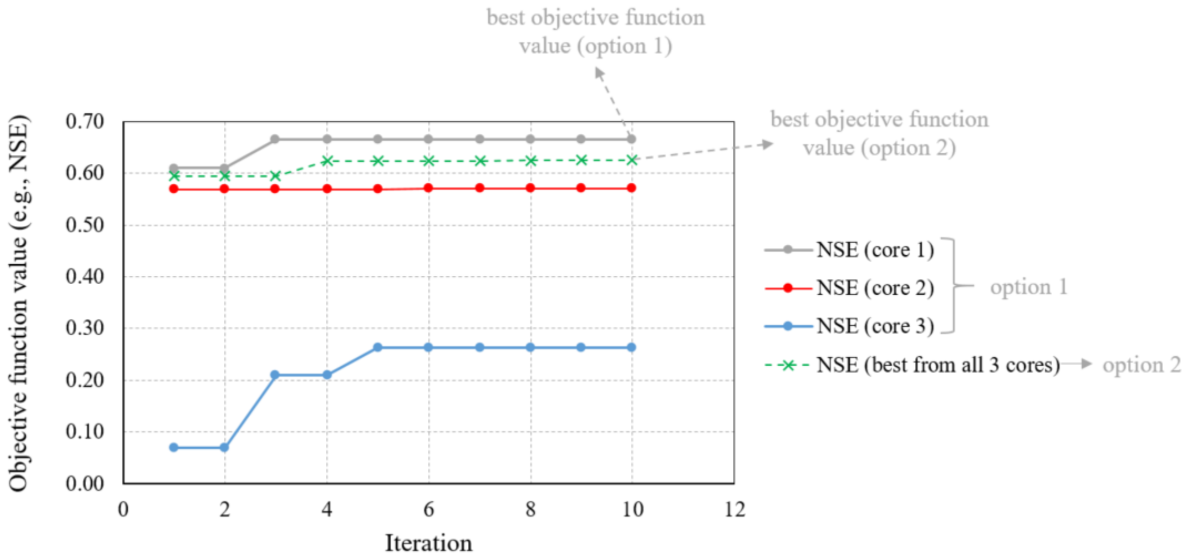

Figure 4. An example of different parallel options when the parameter sets are generated in sequence (e.g., with the DDS approach). These options need to be defined using the drop-down and user-defined setting boxes in Figure 2. A detailed description of the case study and the objective function used in this example is given in Section 3.

Parallel option 1: DDS is run in parallel on each core independently. In other words, there is no communication of the intermediate results among cores. After all iterations (e.g., 10 iterations as in Figure 4) are completed, the best parameter set is the one that gives the best objective function value among all cores.

Parallel option 2: *R-SWAT* evaluates the objective function and finds the best parameter set among all cores after each iteration. This parameter set is assigned as an initial parameter set for all cores in the next run; then, the DDS approach is used (independently for each core) to generate the next parameter set. Thus, after all iterations, the best parameter set is the one that gives the best objective function value.

The efficiency of these different parallel options could vary on a case-by-case basis and this needs to be investigated in future studies.

2.5. Output extraction, model performance evaluation, and uncertainty analysis

R-SWAT is flexible in terms of extracting model outputs after each model run for model performance evaluation. Users can extract model outputs from different SWAT output files (Figure 3) and evaluate the model performance using standard objective functions such as the Nash-Sutcliffe efficiency (NSE, Nash & Sutcliffe, 1970), the Kling-Gupta efficiency (KGE, Gupta et al., 2009), absolute bias (aBIAS), the root mean square error (RMSE, Moriasi et al., 2007) and coefficient of determination (R^2, Krause et al., 2005). In addition, there are options allowing users to define any model outputs and objective functions (*userReadSwatOutput* and *userObjFunction*). A specific R script file (with examples) is provided for users (as specified in the supporting material *R-SWAT.pdf*). Users can modify the script without having to read the entire code of *R-SWAT*. Therefore, evaluating the model performance at different spatial (HRU to basin) and temporal (e.g., daily to yearly) scales is possible. In case the SWAT model is modified and new output files are created, this option can be used to extract model outputs from the new files.

To evaluate the model prediction uncertainty, *R-SWAT* uses the SUFI-2 concept for all parameter calibration/optimization approaches except the GLUE approach (Table 2). The objective of SUFI-2 (Abbaspour et al., 2004) is not to search for an optimal parameter set but instead to cover as much observed data as possible within the 95 percent prediction uncertainty (95PPU) band, with the 95PPU band being as small as possible. The 95PPU band (at 2.5 and 97.5 percentiles of the simulated results at every time step) is calculated based on a given behavioral threshold value of the objective function defined by users. The 95PPU is evaluated using the *r-factor* (the average thickness of the 95PPU band divided by the standard deviation of the measured data) and the *p-factor* (the percentage of measured data bracketed by the 95PPU band) (Abbaspour et al., 2004). With the GLUE approach, the simulated results are sorted according to their likelihood values, and the 95PPU band is calculated with the sorted values (Beven & Binley, 1992).

2.6. Visualization, interactive user interface, and technical support

We use visualization R packages, such as *ggplot2* (Wickham, 2011) and *plotly* (Chang et al., 2021) to facilitate the visual evaluation of model outputs. The model outputs can be evaluated at different spatial (e.g., HRU, subbasin, or basin) and temporal (daily, monthly, or yearly) scales. This allows SWAT modelers to examine the model results, potentially assisting in detecting spatial and temporal issues as well as helping to understand model behaviors.

Users interact with *R-SWAT* via an interactive GUI created with the *shiny* package as shown in Figures 2-3 and in the supporting material (*R-SWAT.pdf*). The user manual was included in the tool; users can click on the "Help" tooltip at each input item to see which input should be provided. To become familiar with *R-SWAT*, tutorial videos and a discussion group were created, where users could directly interact with others and developers.

3. Illustrative examples

In this section, we demonstrate specific functions of *R-SWAT* (e.g., parameter sensitivity and parameter calibration with specific approaches). Running *R-SWAT* with other approaches are highlighted in the user manual (https://github.com/tamnva/R-SWAT/wiki/R-SWAT-User-Manual, accessed 25 March 2022).

3.1. Study area and data

The study area (12°0'18.22"N, 107°41'16.51"E) is the Dak Nong river basin (Figure 5), located in the central highland region of Vietnam. The elevation of the study area ranges from 558 to 1344 m above the mean sea level. Forest (FRSE) and agricultural land (AGRL, mainly coffee and commodity crops (Meyfroidt et al., 2013)) are the two dominant types of land use, accounting for 56.6 and 43.3% of the study area, respectively. The main soil type is Rhodic Ferrasols with a red to dusky red B horizon. The local climate is characterized by a tropical monsoon climate with distinct rainy (April/May to October) and dry seasons (Ngo-Thanh et al., 2018). As a result, the study area's flow regime has high seasonality, with 84% of the annual streamflow occurring in the rainy season.

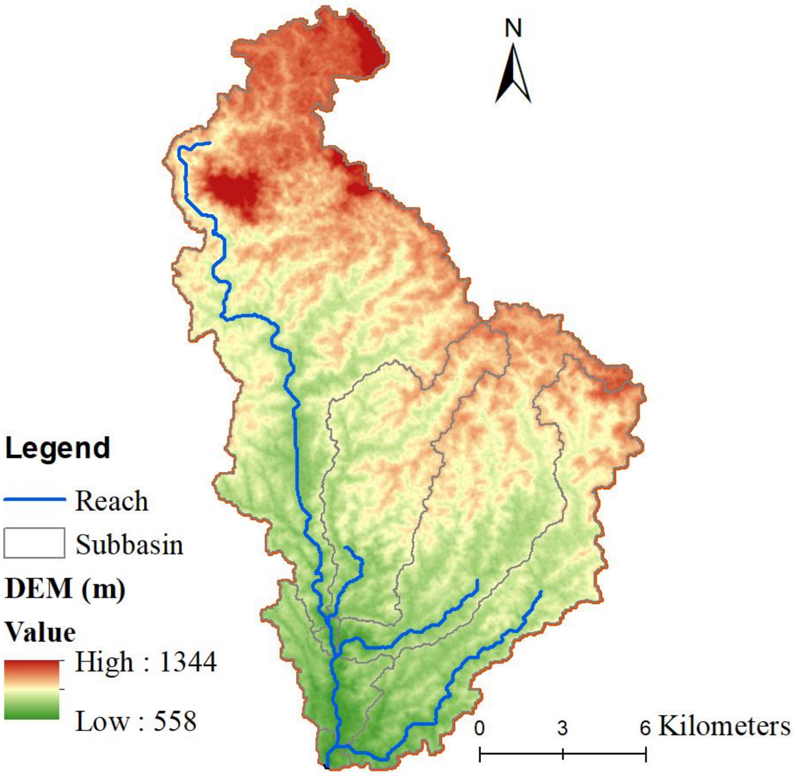

Figure 5. Location and digital elevation model (DEM) of the study area

The digital elevation model (DEM) was obtained from the Shuttle Radar Topography Mission (https://dwtkns.com/srtm30m/). Land use/land cover was derived from Landsat satellite images (www.usgs.gov) using the maximum likelihood classifier. Results of land use classification were qualitatively evaluated using Google Earth images. The soil map was taken from the FAO-UNESCO global soil map (http://www.fao.org). Climate data (daily precipitation, air temperature, and daily observed streamflow at the catchment outlet) were provided by the Viet Nam Meteorological and Hydrological Administration. In this study, daily observed streamflow data at the catchment outlet were used for evaluating the model performance, parameter sensitivity analysis, and calibration.

3.2. Parameter sensitivity analysis

Different parameters were selected to perform sensitivity analysis, to demonstrate the ability of *R-SWAT* in modifying different types of SWAT parameters (Table 3). The selected parameters are also the most commonly used for streamflow calibration (Arnold, Moriasi, et al., 2012). The parameter ranges were taken from literature (Arnold, Kiniry, et al., 2012) and our local knowledge of the study area.

Table 3. List of parameters and their ranges for sensitivity analysis with the Morris approach. The extensions ".gw," ".bsn," ".hru," ".mgt," ".rte," ".sol," and ".sub" indicate the file name extensions in which the respective parameters are located. "All" indicates changes that are applied for all subbasins, land uses, soil types, or slopes, and blank cells indicate that no input is needed. A detailed description of these parameters can be found in Arnold et al. (2013).

Parameters	Change	Min	Max	Subbasin	Land use	Soil	Slope
GW_DELAY.gw	replace	0.5	0.99	All	All	All	All
GW_REVAP.gw	replace	0.02	0.2	All	All	All	All
GWQMN.gw	replace	0	2000	All	All	All	All
RCHRG_DP.gw	replace	0	0.2	All	All	All	All
REVAPMN.gw	replace	0	500	All	All	All	All
SURLAG.bsn	replace	0.1	10				
EPCO.hru	replace	0.01	0.4	All	All	All	All
OV_N.hru	replace	0.01	0.5	All	All	All	All
CN2.mgt	relative	-0.25	0.25	All	All	All	All
CH_K2.rte	replace	0	10	All			
CH_N2.rte	replace	0.025	0.1	All			
SOL_AWC.sol	relative	-0.25	0.25	All	All	All	All
SOL_K.sol	relative	-0.25	0.25	All	All	All	All
CH_N1.sub	replace	0.025	0.1	All			

Sensitivity analysis was performed for the period 2000-2007, including two years (1998-1999) for warming-up. The NSE for streamflow was used to measure model responses to changes in the model parameters for sensitivity analysis. The Morris's elementary effects screening method (Campolongo et al., 2007; Iooss et al., 2021; Morris, 1991) implemented in *R-SWAT* was used for global parameter sensitivity analyses as an example. As an example, 20 trajectories and 14 parameters were selected and consequently 300 simulations were performed for parameter sensitivity analysis. Results from the sensitivity analysis were used to select the six most sensitive parameters (CN2.mgt, CH_N1.sub, CH_K2.rte, OV_N.hru, CH_N2.rte, and GW_REVAP.gw) for model calibration (Figure 6).

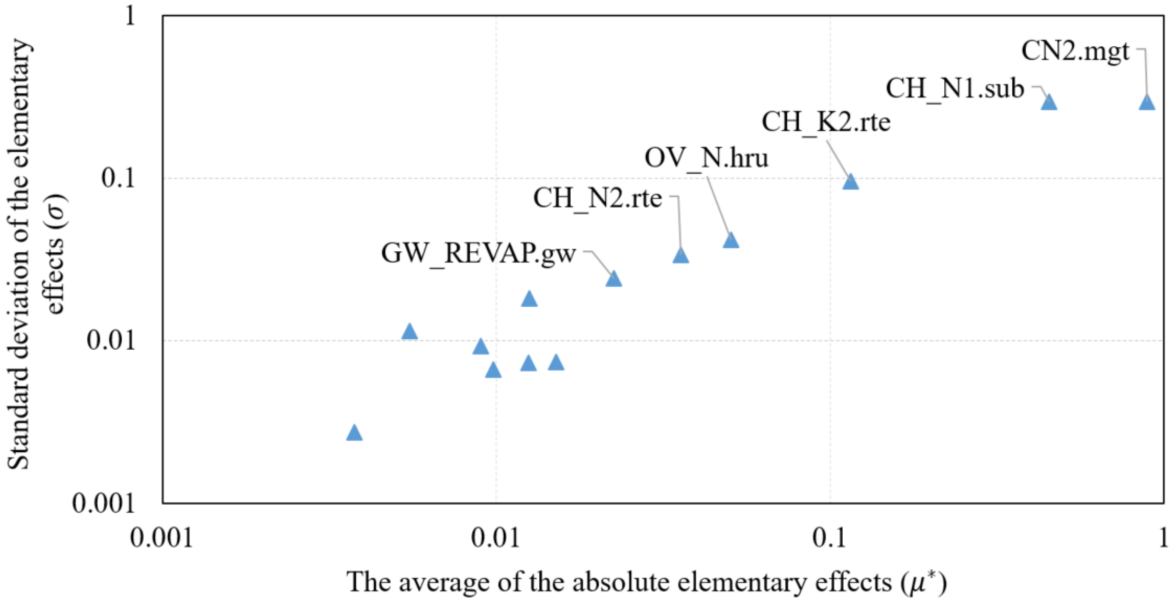

Figure 6. Results of parameter sensitivity analysis using the Morris approach (only the six most sensitive parameters were labeled). In this approach, higher μ^* values indicate higher sensitivity, while higher σ values indicate higher interactions of the respective parameter with others or higher degree of non-linearity in the model response to changes in the values of the specific parameter. "CN2" is the Soil Conservation Service Curve Number II value, "CH_N1" is the Manning's "n" value for tributary channels, "CH_K2" is the effective hydraulic conductivity, "OV_N" is the Manning's "n" value for overland flow, "CH_N2" is the Manning's "n" value for the main channel, and "GW_REVAP" is the groundwater "revap" coefficient (Arnold et al., 2013).

3.3. Parameter calibration and uncertainty analysis

For the model calibration demonstration, we generated 1000 parameter sets using the uniform LHS approach that was implemented in *R-SWAT*. The NSE for streamflow (calculated for the period 2000-2007) was used to evaluate the model performance. Simulations with NSE ≥ 0.65 were defined as behavioral, resulting in a total of 52 simulations. The characteristics of the behavioral parameter sets are presented in Table 4, and the simulated streamflow at the catchment outlet is shown in Figure 7. In general, it can be said that the model was satisfactorily calibrated using *R-SWAT* (*p-factor* = 0.24, *r-factor* = 0.17). However, visual inspection (using the interactive plot option in *R-SWAT*) shows a clear mismatch between the simulated and observed streamflow series at shorter time scales and differences in flow magnitudes, such as the underestimation of low flows (Figure 7b), the overestimation of high flows (Figure 7c), and the presence of high flows in the simulations which does not exist in the observed data (Figure 7d). This could be due to uncertainties either in the observed data or in the model structure that would need further investigation.

Table 4. Characteristics of behavioral parameter sets.

Parameter	Change	95% confidence interval	Median	Best value
CN2.mgt	relative	[-0.25, -0.13]	-0.21	-0.21
CH_N1.sub	replace	[0.07, 0.10]	0.09	0.10
CH_K2.rte	replace	[0.33, 9.61]	6.78	6.48
OV_N.hru	replace	[0.03, 0.49]	0.29	0.26
CH_N2.rte	replace	[0.03, 0.09]	0.06	0.05
GW_REVAP.gw	replace	[0.03, 0.19]	0.11	0.12

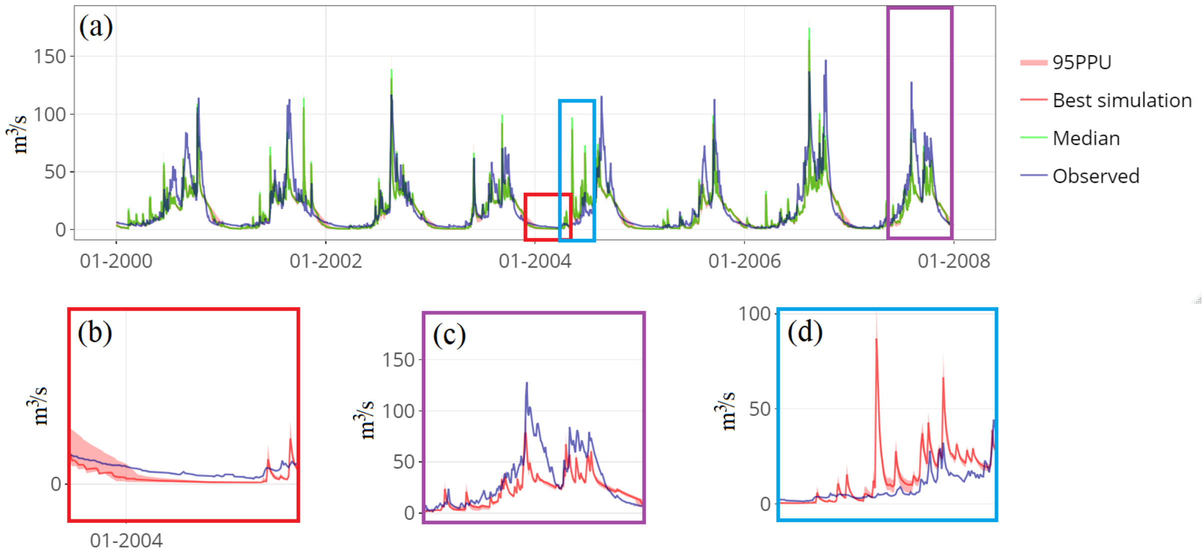

Figure 7. Observed and simulated streamflow (m^3/s) at the catchment outlet a) during the calibration period, b) low-flow, c) high-flow, and d) normal-flow condition (the subfigures were produced by *R-SWAT*).

3.4. Visualization of simulation results

In this study, the results from the best simulation were used to demonstrate the visualization functions of *R-SWAT*. Spatial (2-D) visualization of the model outputs was performed at the HRU and subbasin level with SWAT outputs taken from the *output.hru* and *output.sub* files, respectively (Figure 8). 1-D visualization of the model outputs from *output.rch* and *watout.dat* files are in the supporting material (*R-SWAT.pdf*).

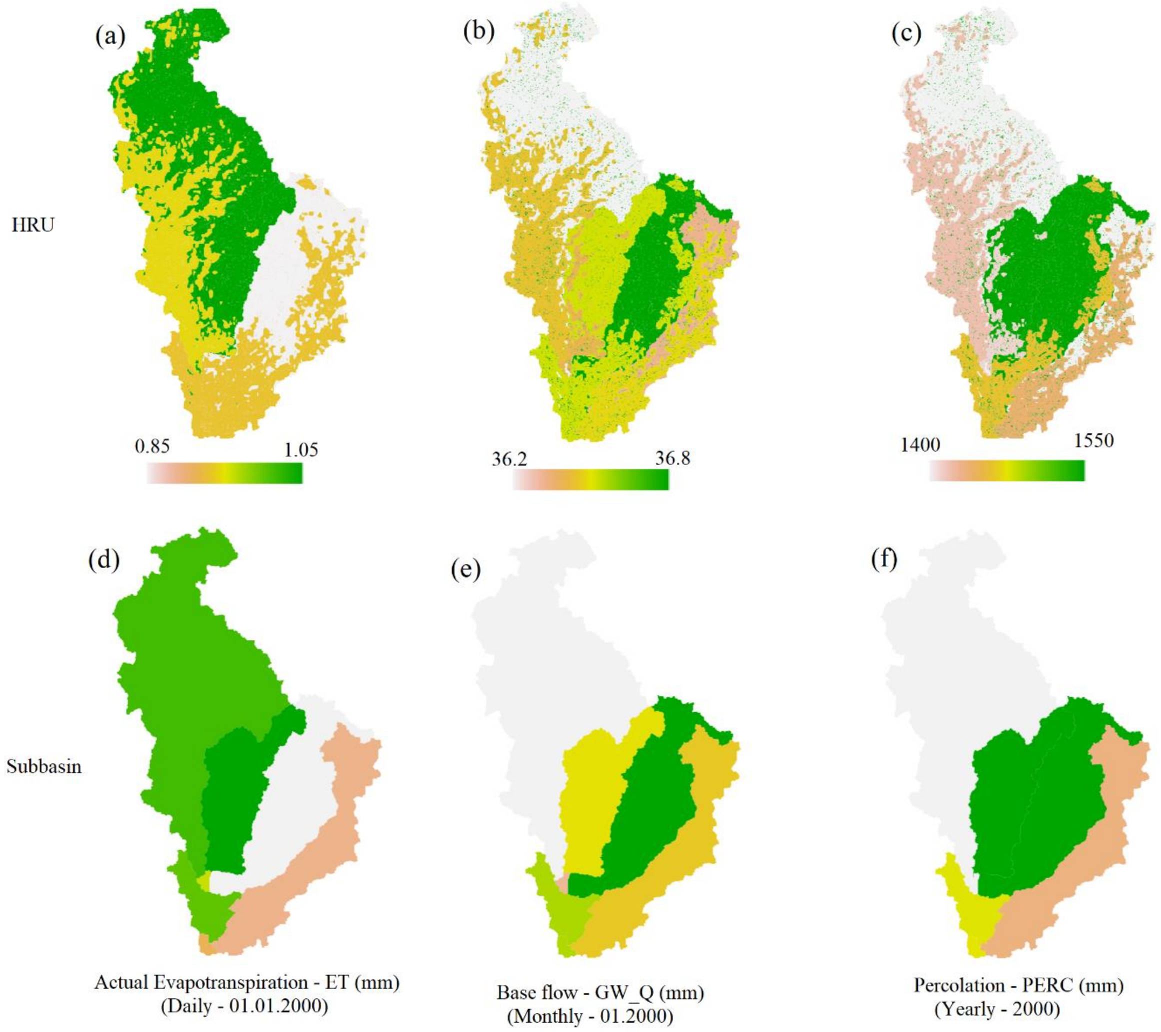

Figure 8. Spatial visualization of SWAT outputs at (a-c) the HRU level and (d-f) subbasin level and at (a, d) daily, (b, e) monthly, and (c, f) yearly time scales for different SWAT output variables (e.g., actual evapotranspiration, baseflow, and percolation). The subfigures were taken from *R-SWAT*.

4. Comparing *R-SWAT* with SWAT-CUP

To demonstrate the validity and effectiveness of *R-SWAT*, we used SWAT-CUP as a benchmark since SWAT-CUP was widely used and well-tested. Specifically, we compare several functions used in *R-SWAT* (version 1.0.0) with the corresponding functions used in SWAT-CUP (version 5.2.1.1). The following aspects were compared between *R-SWAT* and SWAT-CUP: (1) the required time for updating SWAT input files, (2) the simulated streamflow with updated SWAT input files, (3) the results of parameter sensitivity analysis with the multivariate linear regression approach, and (4) the calibrated streamflow statistics with three different calibration approaches (SUFI-2, PSO, and GLUE). In all simulations below, we used the SWAT project setup for the Dak Nong river basin and the model performance was evaluated (if required) using the NSE for daily streamflow at the catchment outlet during the period 2000-2007.

Our results show that the required time for updating SWAT input files with a new parameter set (Table 3) with *R-SWAT* is 0.10 seconds while that with SWAT-CUP is 0.52 seconds (all simulations are performed with the same computer and with one core). Less time is required with *R-SWAT* as it rewrites a file with all updated parameter values at once (Section 2.1). However, SWAT-CUP rewrites a file multiple times depending on the number of updated parameters in that file.

To compare the calibrated streamflows with updated SWAT input files from *R-SWAT* and SWAT-CUP, we generated one random parameter set with the parameters reported in Table 3 and used this parameter set for running both *R-SWAT* and SWAT-CUP. The simulated results (e.g., discharge at the catchment outlet) with the updated input files from *R-SWAT* and SWAT-CUP are similar but not identical (correlation R^2 = 0.99994, Figure 9). This is because *R-SWAT* and SWAT-CUP use different standards for rounding of a 5, e.g., the rounded number of 0.185 with two decimal places in *R-SWAT* and SWAT-CUP is 0.18 (https://stat.ethz.ch/R-manual/R-devel/library/base/html/Round.html, accessed 12 June 2022) and 0.19, respectively. In addition, when writing input files with the updated parameter values, *R-SWAT* uses the number of decimal places as defined in SWAT while SWAT-CUP mostly uses six decimal places). A comparison between the updated files from *R-SWAT* and the original files shows that *R-SWAT* can correctly update SWAT input files with a given parameter set (as demonstrated in the user manual).

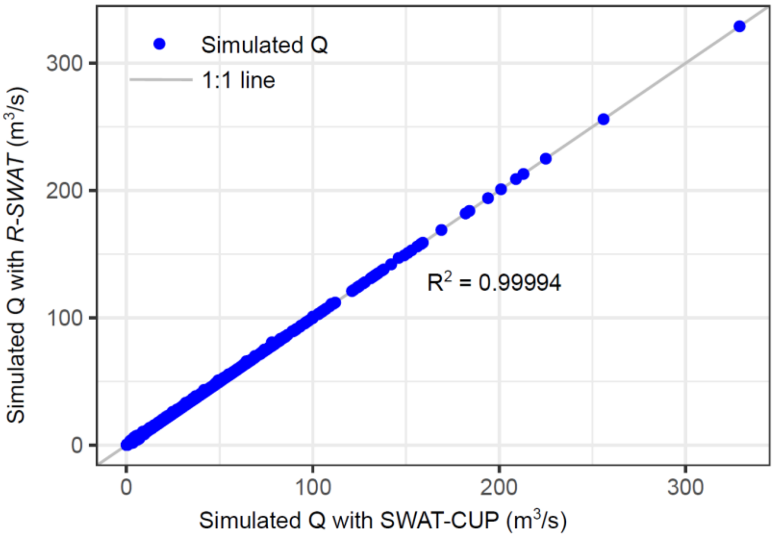

Figure 9. Simulated daily simulated streamflows (Q) at the catchment outlet (during the 2000-2007 period) with updated SWAT input files from *R-SWAT* and SWAT-CUP.

To compare the results of parameter sensitivity analysis by the multivariate linear regression used in *R-SWAT* and SWAT-CUP, we generated 1000 parameter sets within their pre-defined ranges (Table 3) with LHS and then run *R-SWAT* and SWAT-CUP to calculate the objective function (NSE for streamflow at the catchment outlet). Results show that the parameter sensitivity ranking from *R-SWAT* and SWAT-CUP are identical (Table 5). There are minor differences in the *t-stat* and *p-value* (Table 5, numbers in bold), which could be due to round-off and precision errors.

Table 5. Parameter sensitivity ranking with *R-SWAT* and SWAT-CUP (higher absolute *t-stat* values indicate higher sensitive parameters). Differences are marked in bold.

Parameter	*R-SWAT*	SUFI-2	Sensitivity ranking

	t_stat	*p_value*	*t_stat*	*p_value*	
CN2.mgt	-1.79E+02	**2.00E-16**	-1.79E+02	**0.00E+00**	1
CH_K2.rte	2.02E+01	**2.00E-16**	2.02E+01	**0.00E+00**	2
OV_N.hru	1.16E+01	**2.00E-16**	1.16E+01	**0.00E+00**	3
SOL_K.sol	-5.62E+00	**2.45E-08**	-5.62E+00	**2.50E-08**	4
CH_N2.rte	5.36E+00	1.02E-07	5.36E+00	1.02E-07	5
RCHRG_DP.gw	-2.73E+00	6.36E-03	-2.73E+00	6.36E-03	6
GWQMN.gw	-2.66E+00	7.83E-03	-2.66E+00	7.83E-03	7
GW_REVAP.gw	-2.47E+00	1.37E-02	-2.47E+00	1.37E-02	8
GW_DELAY.gw	2.06E+00	3.94E-02	2.06E+00	3.94E-02	9
SOL_AWC.sol	1.74E+00	8.23E-02	1.74E+00	8.23E-02	10
REVAPMN.gw	1.59E+00	1.12E-01	1.59E+00	1.12E-01	11
CH_N1.sub	1.05E+00	2.94E-01	1.05E+00	2.94E-01	12
EPCO.hru	7.71E-01	4.41E-01	7.71E-01	4.41E-01	13
SURLAG.bsn	**-3.00E-03**	9.98E-01	**-2.56E-03**	9.98E-01	14

The comparison of the calibrated streamflow statistics (best NSE, *r-factor*, and *p-factor*) with three different approaches (SUFI-2, GLUE, and PSO) from *R-SWAT* and SWAT-CUP was conducted by calibrating the SWAT model for streamflow (the parameters subjected to calibration were given in Table 3 and their ranges were defined in Table 6). In each calibration approach, the number of model runs is 1000 and the behavioral threshold is NSE = 0.65. Results from *R-SWAT* and SWAT-CUP are comparable and acceptable (Table 6). Minor differences in the results are due to the randomness of the three approaches.

Table 6. Calibrated streamflow statistics with three different calibration approaches (SUFI-2, GLUE, PSO) from *R-SWAT* and SWAT-CUP. Results of the SUFI-2 approach with *R-SWAT* were taken from the previous simulation (Section 3.3).

Calibration approach	*R-SWAT*			SWAT-CUP		
	Best NSE	*r-factor*	*p-factor*	Best NSE	*r-factor*	*p-factor*
SUFI-2	0.67	0.17	0.24	0.67	0.16	0.26
GLUE	0.68	0.17	0.26	0.68	0.16	0.25
PSO	0.68	0.17	0.28	0.68	0.17	0.36

5. Outlook

The primary purpose of *R-SWAT* is to advance hydrological research with SWAT, and R. *R-SWAT* is expected to rely not only on its original developers but also on its community for long-term development. Currently, we included some R functions/packages into *R-SWAT*. Incorporating new packages, e.g., for parameter sensitivity and calibration, will be straightforward since it only requires adding the package name to the *R-SWAT* code (see the supporting material *R-SWAT.pdf*). Therefore, *R-SWAT* is a flexible platform for developing and testing new parameter sensitivity and optimization packages with complex hydrological models (SWAT). Future efforts to improve *R-SWAT* could focus on the following aspects: 1) enabling statistical analysis of the model results using existing R packages, (2) expanding *R-*

SWAT for SWAT+, and (3) creating an R script for running *R-SWAT* in high-performance computing clusters without a graphical user interface.

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