COMPARATIVE ANALYSIS OF SWAT CUP AND SWATSHARE FOR CALIBRATING SWAT MODELS

by

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For my parents

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ABSTRACT

Soil and water assessment tool model (SWAT model) is a widely used model when dealing with large and complex watershed simulations. To correctly predict runoff of a watershed, auto-calibration methods are applied. Among all the platforms, SWAT CUP is widely used in the SWAT model community. The new web-based calibration platform: SWATShare is also gaining its popularity due to the benefits of user-friendly interface, access to high-performance computing resources, and collaborative interface. While the algorithm implemented in SWAT CUP is Sequential Uncertainty Fitting version 2 (SUFI2), Sorting Genetic Algorithm II (NSGA-II) is the algorithm employed by SWATShare. There is a limited amount of research comparing the model performance between these two calibration algorithms and platforms.

This study aims to examine whether the performances of calibrated models are providing equally reliable results. Thirty US watersheds are studied in this research, SWAT models were calibrated using seven years of rainfall data and outflow observations from 2001 to 2007, and then the models were validated using three years of historical records from 2008 to 2010. Inconsistency exists between different algorithms calibrated parameter sets, and the percentage difference between parameter values ranges from 8.7% to 331.5%. However, in two-thirds of the study basins, there is no significant difference between objective function values in two algorithms calibrated models. Correlations are examined using values of parameters and watershed features. Among all the features and parameters, Length of reach and GW_DELAY, CH_N2 and ALPHA_BF, climate zone and GWQMN, SFTMP and NSE have medium correlation exist in both SWATShare and SWAT CUP calibrated models among 30 watersheds. The correlation coefficient difference between them are less than 0.1. When visualizing results by Ecoregions, KGE and NSE are similar in calibrated models from both tools.

The initial parameter range used for SWAT CUP calibration could lead to satisfactory results with greater than 0.5 objective function values. However, the parameter values of the calibrated model might not be presenting a real physical condition since they are out of the realistic range. The inaccurate parameter values might lead to lower objective function values in the validation. The

objective function values can be improved by setting the range of parameter values to match the realistic values.

By comparing two tools, SWATShare accurately calibrates parameter values to a realistic range using default range in most cases. For those models with an unsatisfactory result from SWATShare, the objective function values could be improved after specifying the parameters to the best-fit range given by SWAT CUP results. Also, for those watersheds which have similar satisfactory calibrated objective values from both tools, constraining the parameter to a reasonable range could generate a new calibrated model that performs as well as the original one. Using the approach to constrain parameter values to a realistic range gradually can exclude some statistically satisfactory but physically meaningless models. Comparing two auto-calibration software, SWATShare accurately calibrates parameter values to a realistic range using default range in most cases. Also, in some of the ecoregions, the best parameter sets in SWATShare fall in a more physically meaningful range. Overall, the newly emerged platform, SWATShare, is found to have the capability of conducting good SWAT model calibration.

1. INTRODUCTION

1.1 Introduction

Hydrologic models play a major role in improving our understanding of watershed behavior in response to short and long-term weather or climatic events, land-use changes and other human interventions. To create a hydrologic model with the ability to provide good surface run-off simulation for a watershed, it has to be calibrated by using historical observations. Calibration can be accomplished by manually changing model parameters for simple models such that its results match observed data. However, most models that are used for long term climate and land-use simulations are relatively complex, involving a large number of parameters, typically more than 10, that are difficult to calibrate manually. In such cases, models are calibrated by using computer algorithms through a process referred to as auto-calibration. The objective nature and effectiveness of auto-calibration make it an attractive approach, but numerous publications (Michael and Bosch,2005; Van Liew,2005; Masih,2011; Razavi,2013; Kumarasamy,2018; Ramesh et al., 2020) have highlighted the challenges associated with auto-calibration, including equifinality where many different combinations of parameters lead to statistically equivalently accurate predictions.

Many auto-calibration algorithms have been developed in the past few decades. For example, Duan et al. (1992) developed the Shuffled Complex Evolution (SCE-UA) algorithm. Muleta and Nicklow (2005) applied the Generalized Likelihood Uncertainty (GLUE) method for uncertainty analysis coupled with automatic calibration. Bekele and Nicklow (2007) introduced the Multi-objective automatic calibration method (NSGA-II) to soil and water assessment tool (SWAT) models. Abbaspour (2015) published an article about using SUFI-II in SWAT model calibration. Barnhart and Sawicz (2017) presented MOESHA, a genetic algorithm for automatic calibration and estimation of parameter uncertainty. When more than one algorithm is available for calibrating a hydrological model, which one will generate a robust set of parameters becomes an important question before adopting a particular approach. In the absence of any comparative studies, answering these questions itself may involve more work than addressing the research problem for which the model is developed. Additionally, using and implementing most calibration routines is not an easy task as these procedures may need to be coded or re-coded before execution, depending on when the routines were published, the type of programming language used in implementing them, and the availability of documentation.

Some desktop-based applications are developed to facilitate the calibration process for modelers. For example, the National Weather Service River Forecast System (NWSRFS) calibration system is one of the earliest- developed platforms for auto-calibration. An enhanced system is referred to for now as the Data Display and Analysis Program (DDAP) (Anderson. E, 2002). The desktop-based system has features including a lumped model calibration component and spatial data analysis and distributed model calibration component. The system provides an integrated interface for modelers to analyze data. However, the system is not open source and not continuously maintained. The U.S. Army Engineer Research and Development Center (ERDC) published an automated Model Calibration Software (GSSHA) for Gridded Surface Subsurface Hydrologic Analysis in 2012. This desktop-based software provides modelers the flexibility to choose from different calibration methods and parameters to perform auto-calibration.
A community-contributed toolbox for managing, analyzing, and visualizing WRF-Hydro input and output files: Rwrfhydro is written in R and free to use (McCreight, 2015). Although Wang, J et al. indicated that a parallel calibration utility for WRF-Hydro on high-performance computers is applicable, Rwrfhydro is still desktop-based and is currently minimally supported and rarely updated. Another automatic calibration tool, known as HSPF-SCE, is also developed in R for the calibration of the Hydrologic Simulation Program-FORTRAN (HSPF) model. (Seong et al., 2015) This tool employs the Shuffled Complex Evolution optimization algorithm (SCE-UA) for calibration. Another calibration tool, VIC-Automated Setup Toolkit (VIC-ASSIST), is accessible through a MATLAB user interface. VIC-ASSIST enables users to perform parameter calibration of Variable Infiltration Capacity (VIC) hydrologic and river routing models. (Wi et al. 2017) The tool provides a user-friendly graphical interface. SWAT CUP, which is used for calibrating the Soil and Water Assessment Tool (SWAT) model is a desktop-based windows application and uses the Sequential Uncertainty Fitting algorithm (SUFI2) for autocalibration.

Desktop-based applications, some mentioned above, can significantly reduce the time needed for modelers to write their own code for model calibration, but there are usually some limitations in using them. For example, most desktop-based applications require a particular operating system and can be computationally intensive, thus limiting their use. When computational demand is high, modelers need access to high-performance computing (HPC) resources, which is not always available and/or easy to get. With the increasing demand for open access and reproducibility of research by professional organizations and journals, such as the American Geophysical Union, the use of models and/or calibration routines that are platform-specific with high computational demand is undesirable. When other researchers want to reproduce published results or extend the study, they have to either rebuild the model or try to contact the author. As a result, web-based platforms are now developed for users to overcome some of these limitations and difficulties. Web-based platforms are interactive, fast, hierarchical, and flexible (Kalinin, 2017). Web-based platforms not only make sure the calibration of hydrologic models easier using HPC resources but also enable users to share and visualize their results interactively. One such example is SWATShare, which allows sharing, publication, auto-calibration, and visualization of SWAT models using XSEDE resources.

Table 1-1 Comparison of existing calibration programs

Calibration Platform	Web-based	User-friendly interface (Not code-based)	Access to HPC	Model Sharing	Visualization tool	Open Source	Free access	The latest version released year.	Study
Data Display and Analysis Program (DDAP)	x	√	x	x	x	x	√	2003	Anderson (2002)
Automated Model Calibration Software for (GSSHA)	x	√	x	x	x	x	√	2012	Skahill (2012)
WRF Hydro-R platform	x	x	√	x	x	√	√	2020	McCreight (2015)
HSPF-SCE	x	x	x	x	x	√	√	2015	Seong(2015)
HYPE	x	x	x	x	√	√	√	2015	Lindström(2010)
VIC-ASSIST	x	x	x	x	√	x	√	2017	Wi (2017)
SWAT CUP	x	√	x	x	√	x	√	2019	Abbaspour(2015)
SWATShare	√	√	√	√	√	√	√	2020	Rajib(2016)
√ Indicates the model has the feature, while x suggests the opposite.									

1.2 Study Objectives and Approach

Considering the above discussion on desktop and web-based approaches for model calibration, this study aims to perform a comparison of calibration results using both approaches (SWATShare and SWAT CUP) for the commonly used SWAT hydrologic model. SWAT CUP adopts a widely used Bayesian framework-based algorithm, SUFI2, for surface runoff calibration. The result of the calibration includes the best parameter set according to objective function as well as the best range for each parameter. SWATShare applies a multi-objective evolutionary algorithm, nondominated sorting genetic algorithm II (NSGA-II), for calibration. With Pareto optimal solutions, the algorithm has the ability to increase model performance in large watersheds. SWAT CUP is now the most popular tool in SWAT calibration community while SWATShare is gaining its popularity. However, there are still a limited amount of research focusing on the performance between these two tools. To adjust this phenomenon, this study uses thirty watersheds with varying climate and geography in the United States to compare calibration results from SWATShare and SWAT CUP, and answer the following questions:

1. Which approach, between desktop-based SWAT CUP and web-based SWATShare, provides more robust and reliable calibrations results for the study watersheds?
2. Which approach yields parameter values that are more representative of the physical characteristics of the study watersheds? Is any approach sensitive to specific geographic or climatic conditions?

The above questions are answered by comparing and analyzing parameter sets and features of 30 watersheds used in SWAT models. These models are created by the ArcSWAT tool in ArcGIS Desktop. Twenty-four out of thirty models are available on the SWATShare platform, and the rest are created during the research. All of the watersheds are delineated using existing USGS gaged locations with at least ten years of data available since 2001.

1.3 Thesis Organization

This study is divided into six chapters. This chapter discusses the study approach, background, and research objectives of this study. The second chapter includes reviews of previous case studies about SWAT models and calibration algorithms. Chapter three focuses on the study area and the data used during the research process. Chapter four presents the methodology and the analysis techniques used in this study. The methodology includes two different calibration algorithms that are used for SWAT model calibrations. Chapter five includes the obtained results and further discussion. The results are divided into two parts based on the calibration method used. Also, Chapter five discusses the results and compares the different techniques used during the process and visualize the results. The last part of this chapter develops a potential approach to improve the results of calibration. The final Chapter six is the summary and conclusions of this study.

2. SWAT MODELING - REVIEW

2.1 Introduction

Soil & Water Assessment Tool (SWAT) is a river basin scale model developed to quantify the impact of land management practices in large, complex watersheds. As a continuous-time model, the objective of SWAT is to predict the long-term response in large basins. SWAT can also help in assessing environmental policies. With a vast set of parameters, the SWAT model provides distributed descriptions of hydrologic processes at the sub-basin scale (Arnold et al., 1998; Neitsch et al., 2011. The first version of SWAT was developed in the early 1990s (Engel et al. ,1993). Gassman et al. (2007) presented a review of over 250 SWAT applications that were created worldwide. As of May 2020, more than 3400 peer-review articles have been published. The SWAT model is a comprehensive model that requires a lot of background information such as initial subbasin topographic criteria, land use, and soil type. Within a SWAT model, Hydrologic Response Units (HRU) are formed based on soil type and land use. The same HRU is assumed to be homogeneous in hydrologic response to land cover change during simulations.

Several studies suggested that to obtain a well-performing calibrated model, setting a reasonable range of parameters is important. (Kennedy, J., 1995; Abbaspour, K.C., 2011; Kayastha et al., 2011; Zhang et al., 2012) Among all the parameters, some of which can be fixed based on existing catchment data (Me, W. et al., 2015) or knowledge gained in other studies. Range of values for other parameters needs to be assigned during the calibration process. (Boyle et al., 2000). The range of parameter values assigned during calibration is lumped. The designated range is an approximation for real value, which varies within a study area. The range of some parameters tends to be subjective. Cibin et al. (2010) found that the best-fit calibrated values for hydrological parameters varied with different flow regimes. Based on other researches, parameter values of the SWAT model can be set according to hydrological characteristics. Yilmaz et al., (2008) suggested, assigning separate parameter values to low, medium, and high discharge periods will benefit the result of calibration. Also, Choi and Beven (2007) found that some parameter values for calibration can be categorized based on the dry, drying, wet, or wetting state of the watershed.

Multiple objective functions and algorithms could be used in model calibration. Different algorithms and range of parameters can produce statistically similar calibration and validation results, but the best-fit parameter set will not necessarily be identical. This is one of the uncertainties during the calibration process. It is known that different sets of parameters, even different model structures, can result in equally good results (Wagener et al. 2003). This behavior is referred to as equifinality (Beven, 2006). The calibrated results could be meaningless even if the validation gives us similar results. Clark and Vrugt (2006) found that the range of parameters for calibration could result in physically unrealistic calibrated parameters. To avoid the problem, an analysis of the solutions and a guided calibration of results is necessary. (Munoz, et al., 2014) Hooshmand et al. used SUFI-2 with different objective functions to calibrate discharge in two watersheds in Iran. In their research, each objective function found an acceptable solution, but with different parameter sets.

For a hydrologic model like SWAT, one parameter set results in a single output. However, when calibration is an inverse process to obtain the parameter values, the observed output could be reached with an infinite number of different parameter sets. This non-uniqueness, which is equifinality of the system, is a property of model calibration in distributed hydrological applications. Beven (2001) stated that, whether a model could be immune to the problem of equifinality during the application to particular catchments with their characteristics is still doubtful. The limited measurements and the condition of subsurface will result in equifinality. To limit the non-uniqueness problem, Abbaspour et al. (2018) suggested that researchers should include multiple observations in the calibration process or constrain the objective function with soft data. The soft data are usually referring to knowledge of local conditions on soil conditions from different land-uses, moisture, and canopy type.

2.2 SWAT Model Parameters

The 19 parameters that are used in SWAT model calibrations are described below and Table 2-1is the normal range and the usage of the parameters.

Table 2-1 Definition of parameters and their range

Parameter Name	Typical Lower Bound	Typical Upper Bound
CN2 Initial SCS runoff curve number for moisture condition II	1	100
GW_DELAY Groundwater delay [days]	1	100
ALPHA_BF Baseflow alpha factor [days]	0.1	1
GWQMN Threshold depth of water in the shallow aquifer required for return flow to occur [mm]	0.01	5000
GW_REVAP Groundwater "revap" coefficient	0.01	0.2
REVAPMN Threshold depth of water in the shallow aquifer for "revap" to occur [mm]	0	500
CH_N2 Manning's n value for main channel	0	100
CH_K2 Effective hydraulic conductivity [mm/hr]	0	100
CANMX Maximum canopy storage [mm]	0	25
ESCO Soil evaporation compensation factor	0.01	1
EPCO Plant uptake compensation factor	0.01	1
SFTMP Snowfall temperature [ºC]	-5	5
SMTMP Snow melt base temperature [ºC]	-5	5
SMFMX Melt factor for snow on June 21 [mm H2O/ºC-day]	0	10
SMFMN Melt factor for snow on December 21 [mm H2O/ºC-day]	0	10
TIMP Snowpack temperature lag factor	0.01	1
SURLAG Surface runoff lag time [days]	0	24
SOL_AWC Available water capacity of the soil layer [mm H2O/mm Soil]	0.01	200
SOL_K Saturated hydraulic conductivity [mm/hr]	0.01	200

CN2 stands for the Initial SCS runoff curve number for moisture condition II. The SCS curve number is related to the soil’s permeability, land use, and soil water conditions. The initial values of CN2 vary in different HRUs in a watershed. In HRUs with urban areas, the model will adjust the curve number to reflect the impact of the impervious areas required. (Pitt, R., 1979)

GW_DELAY stands for groundwater delay days, which is the lag between the time water moves past the underground and enters the shallow aquifer. Sangrey et al. (1984) noted that the same area tends to have similar values for groundwater delay, so when a delay time value is defined, a comparable value can be used in adjacent areas.

ALPHA_BF is the baseflow recession constant, as known as a direct index of groundwater flow response to changes in recharge (Smedema and Rycroft, 1983).

GWQMN is the threshold depth of water in the shallow aquifer required for return flow to occur. The value represents the millimeter of H2O in the aquifer. When the depth of water in shallow aquifer is less than the value presented, groundwater will not flow to reach.

GW_REVAP is the groundwater "revap" coefficient. As the water evaporates from capillary fringe or evapotranspiration occurs, water underneath will replace the void. If GW_REVAP is close to zero, the movement of water is restricted. While GW_REVAP is close to 1, the rate of water transfer approaches the rate of evapotranspiration.

REVAPMN is the threshold depth of water in the shallow aquifer for “revap” or percolation to the deep aquifer to occur; the value represents millimeter of H2O. Water flows from shallow aquifer to deeper aquifer only if REVAPMN is less than the value in the shallow aquifer.

CH_N2 is the manning's "n" value for the main channel and CH_K2 is the effective hydraulic conductivity in the main channel. For streams that have continuous groundwater discharge, the effective conductivity will be zero.

CANMX is the maximum canopy storage represents in mm H2O that can describe the maximum amount of water that can be trapped by the canopy. Coverage of canopy will significantly affect infiltration, surface flow, evaporation, and evapotranspiration. The influence is related to the density of coverage and the plant species.

ESCO is the soil evaporation compensation factor. ESCO is automatically set to 0.95 if no values are entered. The normal range of ESCO is between 0.01 and 1.0. The lower ESCO, the model will have the ability to extract more of the evaporative demand from lower levels. (Sharpley, et al., 1982)

EPCO is the plant uptake compensation factor. It describes the amount of water that goes up on a given day. If upper layers of soil do not contain enough water for water uptake, this factor allows lower layers to compensate. The value should range from 0.01 to 1.00. If EPCO is unknown, the value will be set to 1.0, indicating the model allows more of the uptake demand.

SFTMP is the snowfall temperature in Celsius, which is the mean air temperature when precipitation is snow or freezing rain. The snowfall temperature should be between –5 ^{o}C and 5 ^{o}C and the default value for SFTMP is 1.0.

SMTMP is the Snowmelt base temperature in Celsius. The snow melts only when the temperature exceeds the given SMTMP. This value should be in the range from –5 ^{o}C to 5 ^{o}C and the default is 0.50.

SMFMX is the melt factor for snow on June 21, the unit is mm H2O/^{o}C-day and the default value is 4.5. In the northern hemisphere, SMFMX is the maximum melt factor, while in southern hemisphere, SMFMX is the minimum melt factor. In rural areas, the melt factor will vary from 1.4 to 6.9 mm H2O/day-°C (Huber and Dickinson, 1988), while in urban areas, the value will be higher due to the compression effect by vehicles.

SMFMN is the melt factor for snow on December 21, the unit is mm H2O/^{o}C-day and the default value is 4.5. In the northern hemisphere, SMFMN is the minimum melt factor, while in southern hemisphere, SMFMN is the maximum melt factor.

TIMP is the snowpack temperature lag factor, the default value for TIMP is 1.0. This factor represents the effect of the snowpack temperature from yesterday, affecting the snowpack temperature of the current day. This factor is a function of snow density and snow depth. The range of TIMP is from 0.01 to 1. The higher the value is, the effect from the previous day is more significant.

SFTMP, SMTMP, SMFMX, SMFMN, and TIMP are important parameters in watersheds where snowfall is significant.

SURLAG is the surface runoff lag coefficient and the default value is 4.0. This parameter describes the fraction of water that flow into reach each day. In a large watershed, the time of concentration is usually greater than one day. The higher the value is, the less amount of water is held in storage.

SOL_AWC is the available water capacity of the soil layer. The unit of the value is mm H2O/mm soil. AWC = FC −WP where AWC is the plant available water content, FC is the water content at field capacity, and WP is the water content at permanent wilting point. (NRCS, 1996) This value varies in different HRUs.

SOL_K is the Saturated hydraulic conductivity with the unit in mm/hr. This value varies in different soil groups.

2.3 Different Algorithms for SWAT Model Calibration

The SWAT input parameters must be constrained within a realistic range when performing SWAT calibration. It is necessary to identify critical parameters and the parameter precision for calibration (Ma et al., 2000). That is, before calibrating a SWAT model, modelers need to decide which parameters to be included during the calibration process either based on their experience or from the results of sensitivity analysis.

Some studies analyzed the influence of HRUs in the model calibration process. Most of the studies focus on streamflow predictions for a watershed ranging from 20 to 18,000 square kilometers (Gassman et al., 2007, Bieroza et al., 2014, Me et al., 2015). For the calibration, the SWAT CUP is the most used software. Currently, the software supports SUFI2 (Abbaspour et al., 2007), GLUE (Beven and Binley, 1992), and ParaSol (van Griensven and Meixner, 2006). SUFI2 is a Bayesian framework-based algorithm widely used for surface runoff calibration. After deciding objective function and parameter range, the algorithm gives a parameter set using Latin hypercube sampling and the resulting 95% predictive interval of each parameter are calculated. Two factors are considered when quantifying uncertainties of a model: The P-factor is the percentage of observed data enveloped in 95% prediction uncertainty (PPU), which is determined at the 2.5% and 97.5% levels of the cumulative distribution of output variables. The r-factor is calculated by dividing the average thickness of the 95PPU band by the standard deviation of the observed data (Abbaspour et al., 2011). The result of the calibration includes the best parameter set according to objective function as well as the best range for each parameter. While SWAT CUP is widely used for SWAT model calibration, it is not using multi-objective calibration algorithms or genetic calibration approaches. (Abbaspour,2013)

Another auto-calibration tool for SWAT model is SWATShare, a cyber-enabled platform that opens for users to upload and share SWAT models and perform calibration. (Rajib.A. et al., 2015) The algorithm applied in SWATShare is nondominated sorting genetic algorithm II (NSGA-II). NSGA-II is a multi-objective evolutionary algorithm that has the ability to increase calibrated model performance in large watersheds (Andersen et al., 2001). While the conventional multi-objective evolutionary algorithms are criticized for their computational complexity, it still provides a fast sorting approach to deal with problems. This feature makes it easier to be mapped with parallel computing resources. (Deb et al., 2002) Some research works have shown that NSGA-II is an effective calibration algorithm for hydrological models. (Getahun and Nicklow, 2007; Shafii and Smedt, 2009; Kayastha et al., 2011; Zhang et al., 2012). Although SUFI2 and NSGA-II algorithms are both used for hydrological model calibration, there is a limited amount of research comparing the model performance between these two calibration algorithms.

Some other algorithms can be applied while calibrating hydrological models. For example, the Generalized Likelihood Uncertainty Estimation method (GLUE) relies on the output of Monte Carlo simulations. After a global best-fit parameter set is developed, the assessments of parameter uncertainty are compared to that set of optimized parameters. In GLUE, all sources of uncertainty (i.e., input uncertainty, structural uncertainty, and response uncertainty) are also accounted for by parameter uncertainty. Since GLUE relies on the concept of non-uniqueness, different parameter sets can result in equally reasonable model predictions. GLUE finds a set of models that perform equally reliable results concerning data available. During the GLUE calibration, a collection of models are simulated with different randomly assigned parameter values.

Besides GLUE, the Particle Swarm Optimization (PSO) is a population-based optimization technique that also have the ability to calibrate hydrological models. Starting with a group of random particles (parameter values) moved around in the search space according to a few simple formulas. (Zhang, Y., 2015), PSO describes the position of particles (coordinate of the parameters) and their velocities and updates the velocity of each particle using the information from the best fit solution so far and examines the performance of the new parameter set. The choice of PSO parameters can have a significant impact on optimization performance. Thus, how to Select PSO parameters that yield good performance has been the subject of much research. The PSO method is often cited in the literature and reported to have been applied to solve numerous problems that arise in real life. (Lindfield, 2017)

Another algorithm is the Parameter Solution (ParaSol). The algorithm minimizes objective functions or obtain a globally optimized criterion by using Shuffled complex evolution (SCE-UA) (Van Griensven and Meixner, 2006). The SCE-UA method is a global search method to minimize a single objective function by adapting competitive complex evolution (CCE) algorithm to update each complex (Duan et al, 1994). The technique has been widely used in watershed model calibration and other areas of hydrology (Abbaspour et al., 2011; Wu, 2015; Khoi,2015; Emam,2018; Melesse et al., 2019)

Other researches had focused on the comparison of different algorithms. Arsenault et al., compared ten algorithms in terms of output performance. Wu and Chen compared three calibration algorithms used in SWAT CUP software. (SUFI-2, GLUE, and ParaSol) and suggested that SUFI-2 was able to provide reliable and predictive results than the other two methods. Kouchi et al., focus on the GLUE, SUFI-2, and PSO algorithms to examine the sensitivity of optimized model parameters as well as objective functions in different optimization algorithms.

Most of the comparisons mentioned above focused on the performance of algorithms implemented in SWAT CUP. While SWAT CUP is widely used in the SWAT model community, the new web-based calibration platform: ”SWATShare” is also gaining its popularity due to the benefits of user-friendly interface, and access to high-performance computing resources. With numerous studies on different calibration methods for SWAT models, there is still a limited amount of literature focus on the performance between SWAT CUP and SWATShare. By comparing the performance of these two platforms, the reliability of SWATShare can be quantified.

3. STUDY AREA AND DATA

3.1 Introduction

This chapter provides an overview of the thirty watersheds that are considered in this study. These watersheds are located in different climate zones, as well as various ecoregions. A description of the data used for building SWAT models, historical observations for calibration, and geographical features for categorization are presented. This includes Digital Elevation Models (DEMs) from National Elevation Dataset (NED); land use from National Land Cover Database 2011 (NLCD 2011); soil data from the State Soil Geographic Database (STATSGO); precipitation and temperature data from the United States Department of Agriculture (USDA), agricultural research service; streamflow data from the USGS historical observation database and topographic data extracted from DEMs.

3.2 Study Area

This study involves 30 different watersheds delineated using USGS gauged outlets, all of the basins are larger than 1000 square kilometers and located on the continental United States, spreading in different climate zones and ecoregions. (see **Error! Reference source not found.**). Among 30 watersheds, 15 of the basins are in the humid continental climate zone, 14 of the watersheds are in the humid subtropical climate zone, one watershed is in the Mediterranean zone. According to the EPA categorized continental United states Ecoregions LevelII, all the studied watersheds spread in ten different ecoregions, including Southern Coastal Plain (SCP), Southeastern Plains (SP), Piedmont (P), Ridge and Valley (RV), Sierra Nevada (SN), Northern Piedmont (NP), Northern Allegheny Plateau (NAP), Northeastern Highlands (NH), Acadian Plains and Hills (APH), and Southeastern Plains (SP). Detailed information about watersheds can be found in Table 3-1.

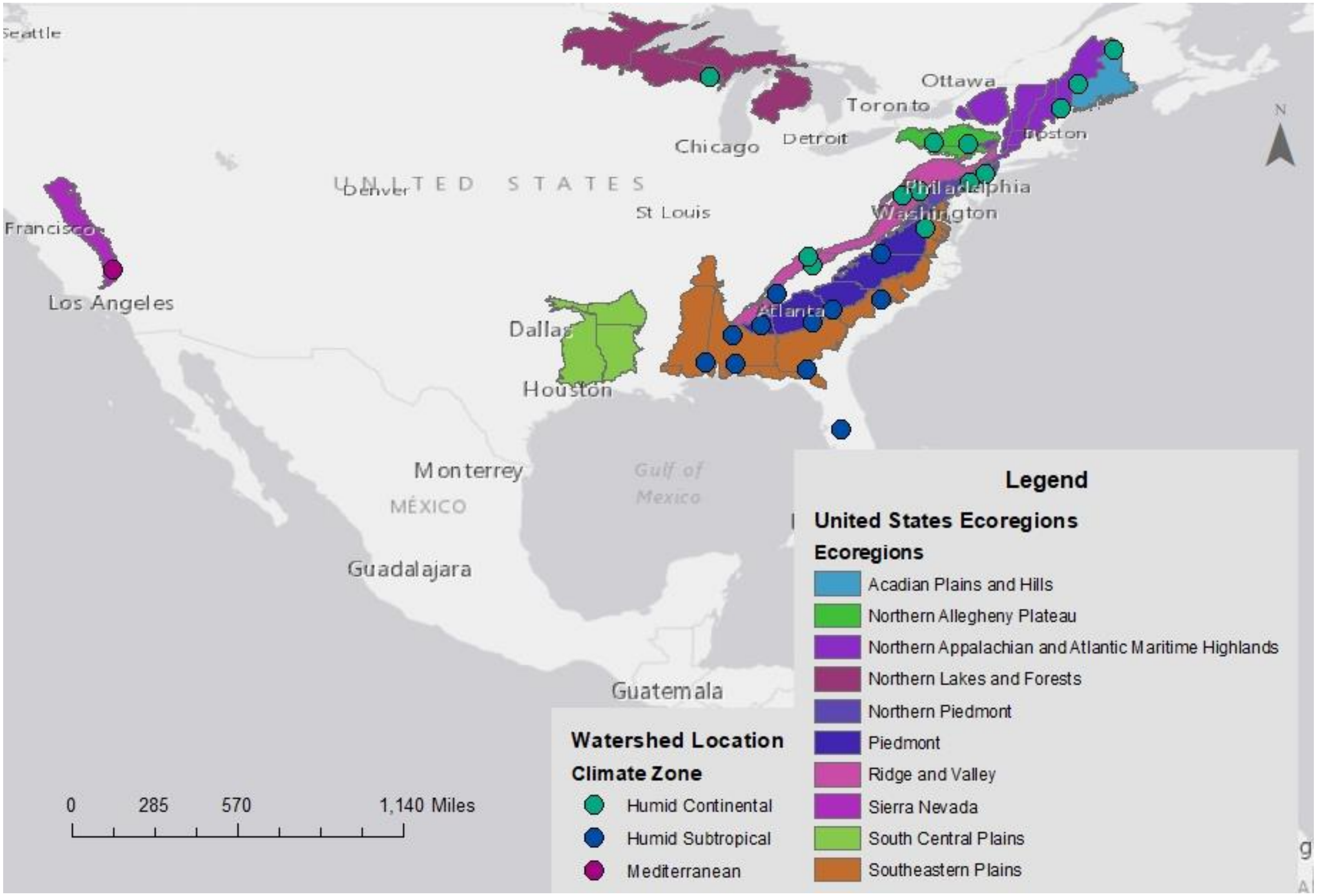

Figure 3-1 Distribution of study watersheds in different climate zones and Ecoregions

Table 3-1 Climate zones and Ecoregions of study watersheds

weather zone	Ecoregion	Station Number	Station Name	State	Area km^2
Humid Continental	Acadian Plains and Hills (APH)	1046500	KENNEBEC RIVER AT BINGHAM	ME	7031.58
		1017000	AROOSTOOK RIVER AT WASHBURN	ME	4283.69
		1030500	MATTAWAMKEAG RIVER NEAR MATTAWAMKEAG	ME	3672.48
	Northeastern Highlands (NH)	1066000	SACO RIVER AT CORNISH	ME	3348.74
		1054000	ANDROSCOGGIN RIVER NEAR GORHAM	NH	3524.85
	Northern Allegheny Plateau (NAP)	1426500	WEST BRANCH DELAWARE RIVER AT HALE EDDY NY	NY	1542.95
		1526500	TIOGA RIVER NEAR ERWINS NY	NY	3566.29
	Northern Lakes and Forests (NLF)	4067958	PESHTIGO RIVER NEAR WABENO, WI	WI	1183.33
	Northern Piedmont (NP)	1473500	SCHUYLKILL RIVER AT NORRISTOWN, PA	PA	4558.22
		1400500	RARITAN RIVER AT MANVILLE NJ	NJ	1273.55
	Piedmont (P)	1672500	SOUTH ANNA RIVER NEAR ASHLAND, VA	VA	1022.87
	Ridge and Valley (RV)	3455000	FRENCH BROAD RIVER NEAR NEWPORT, TN	TN	4812.03
		3528000	CLINCH RIVER ABOVE TAZEWELL, TN	TN	3817.51
		1608500	SOUTH BRANCH POTOMAC RIVER NEAR SPRINGFIELD, WV	WV	3783.84
		1614500	CONOCOCHEAGUE CREEK AT FAIRVIEW, MD	MD	1296.62
Humid Subtropical	Piedmont (P)	2414500	TALLAPOOSA RIVER AT WADLEY AL	AL	4338.08
		2414715	TALLAPOOSA RIVER NR NEW SITE, AL. (HORSESHOE BEND)	AL	5330.01
		2223000	OCONEE RIVER AT MILLEDGEVILLE, GA	GA	7640.21
		2196000	STEVENS CREEK NEAR MODOC, SC	SC	1409.04
		2074000	SMITH RIVER AT EDEN, NC	NC	1408.22
	Ridge and Valley (RV)	2387500	OOSTANAULA RIVER AT RESACA, GA	GA	4149.02
	Southeastern Plains (SP)	2473000	LEAF RIVER AT HATTIESBURG, MS	MS	4527.15
		2374250	CONECUH RIVER AT STATE HWY 41 NEAR BREWTON, AL.	AL	6891.72
		2478500	CHICKASAWHAY RIVER AT LEAKESVILLE, MS	MS	6966.83
		2130980	BLACK CREEK NEAR QUINBY, SC	SC	1137.83
		2425000	CAHABA RIVER NEAR MARION JUNCTION AL	AL	4573.76
		2318500	WITHLACOOCHEE RIVER AT US 84, NEAR QUITMAN, GA	GA	3833.05
	Southern Coastal Plain (SCP)	2317500	ALAPAHA RIVER AT STATENVILLE, GA	GA	3548.16
		2294898	PEACE RIVER AT FORT MEADE FL	FL	1127.93
Mediterranean	Sierra Nevada (SN)	1189500	RARITAN RIVER AT MANVILLE NJ	CA	1371.51

3.3 Data

3.3.1 SWAT Models from SWATShare

SWATShare is an internet-based platform that enables users to upload, share, and execute hydrologic models being created in Soil and Water Assessment Tool. (Rajib.A, 2015) It provides an open platform for users to calibrate, visualize, and share their SWAT models. This study involves 24 open sources SWAT models from SWATShare, which were developed in the CE549 Computational Watershed Hydrology course at Purdue University in 2018 and 2019. The rest of the models are created during the research. All of the models share identical Digital Elevation, soil, and land use data sources.

3.3.2 Digital Elevation Model

Digital Elevation Models (DEMs) of all basins are used for watershed delineations. The 30-m horizontal resolution DEMs from National Elevation Dataset (NED) are available on the United States Geological Survey, TNM download V1.0.

3.3.3 Land Use and Soil Data

Land-use data of watersheds are needed for building SWAT models. Land-use data from the National Land Cover Database 2011 (NLCD 2011) are used in this study. NLCD 2011 covers land use information of 49 States in the United States and available for users to gather the 30-m resolution land cover data. The information on dominant land use is extracted for feature correlation analysis, and lands are categorized into four different land-use types: Water, Medium Residential, Forest, Agricultural, based on their dominant land use. When one of the land use types covers over 30% of the total area in a basin, that land-use type is defined as dominant land use of the watershed. The information can be found in **Error! Reference source not found.**.

State Soil Geographic Database (STATSGO) database, a digital general soil association map developed by the National Cooperative Soil Survey, is also used in this study.

3.3.4 Precipitation and Temperature Data

The historical precipitation and temperature record between the years 2001 to 2010 are clipped for SWAT model simulations. The daily data are obtained from the United States Department of Agriculture (USDA) Agricultural research service, which has county-level daily precipitation and temperature information dated from 1990 to November 2013.

3.3.5 Streamflow Data

The Historical averaged daily streamflow data of the year 2001 to 2010 are obtained from the USGS historical observation database for calibration and validation purposes. The peak outflow rate, minimum outflow rate, maximum outflow rate, and standard deviation of study rivers are also extracted for the feature correlation analysis. The Station numbers and names are listed in Table 3-1.

3.3.6 Topographical Data

Topographical data, including reach length, averaged slope of the river, drainage density of basins are extracted from DEMs for feature correlation analysis, Topographical information can be found in Table 3-2

Table 3-2 Topographical data and dominant land use

Dominant Land Use	Watershed Station number	Reach Length (KM)	River Slope	Drainage Density
Agriculture	**2294898**	131.46	0.02	0.12
	2130980	198.93	0.03	0.17
	1189500	196.44	0.09	0.15
	1614500	181.15	0.05	0.04
	2425000	289.24	0.02	0.06
	2318500	402.54	0.02	0.11
	2317500	511.07	0.05	0.07
Forest	**2414500**	485.97	0.06	0.07
	2473000	405.59	0.09	0.08
	2374250	575.41	0.07	0.08
	2478500	147.84	0.06	0.1
	2414715	343.5	0.14	0.08
	2223000	910.04	0.28	0.19
	2196000	402.61	0.3	0.11
	2387500	142.17	0.18	0.1
	3455000	147.75	0.06	0.14
	3528000	363.53	0.23	0.1
	2074000	267.79	0.1	0.06
	1672500	165.14	0.07	0.13
	1608500	118.51	0.18	0.08
	1473500	272.58	0.15	0.08
	1400500	217.05	0.14	0.06
	1426500	258.85	0.04	0.07
	1526500	228.41	0.13	0.06
	1066000	312.2	0.1	0.04
	1030500	183.78	0.04	0.16
	1054000	264.8	0.05	0.06
	1046500	131.46	0.02	0.12
	4067958	198.93	0.03	0.17
	1017000	135	0.24	0.1

4. METHODOLOGY

4.1 Methodology Overview

This chapter describes the methodology followed in this study, which can be divided into four steps: (1) Establish SWAT models using land-use data, soil data, and the outlet location; (2) Calibrate models in SWAT CUP and SWATShare using meteorological data and historical outflow observation; (3) Validate models using meteorological data, outflow observation in a different period; and (4) Extract the calibrated parameter sets and compare the results from SWAT CUP and SWATShare.

Soil, land use, and meteorological data are preprocessed and converted into the desired format when building SWAT models. The parameter sets and range are identical for both SWATShare and SWAT CUP calibration process. After the calibrations, validations are performed to confirm the reliability of calibrated models. Also, parameters are extracted and categorized for analysis. The process is shown in Figure 4-1 Research process below.

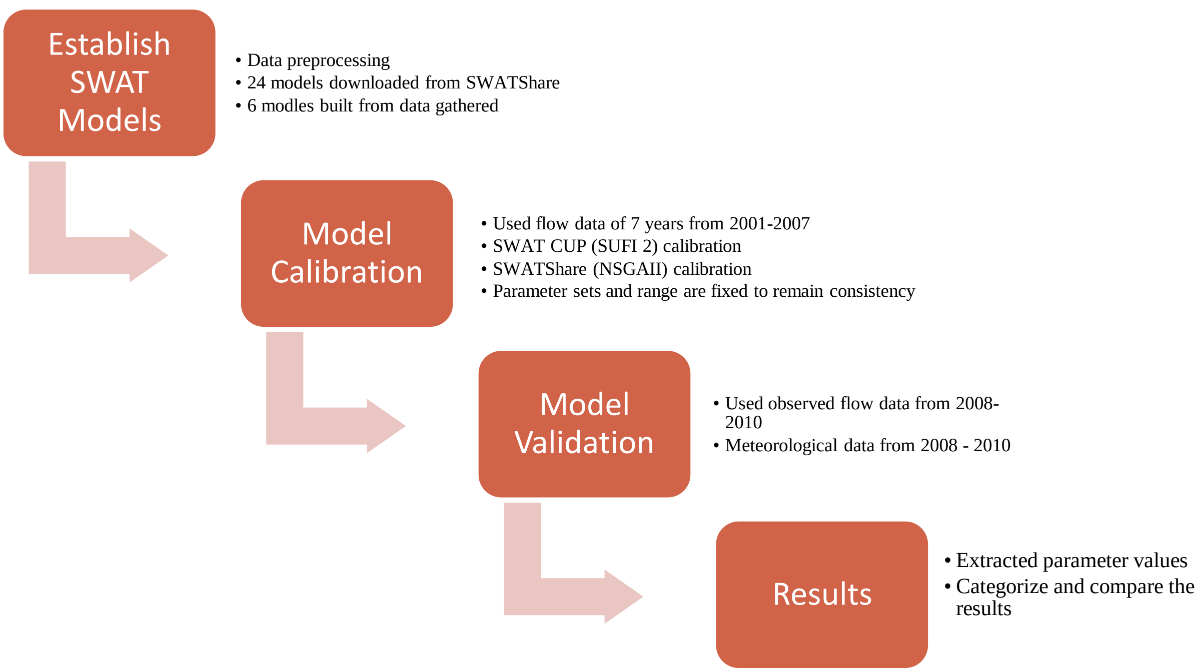

Figure 4-1 Research process

4.2 Establishing SWAT Models

4.2.1 Data Preprocessing

All of the SWAT models used for the study are created using ArcSWAT in Arc GIS version 10.5.1. Twenty-four out of thirty SWAT models used in this study are available on the SWATShare platform while the rest are newly built during the research. With soil data extracted from the STATSGO database in different watersheds and land use data from the National Land Cover Database 2011 (NLCD 2011), hydrologic response unit (HRU) in SWAT models are created. Weather data including relative humidity, solar radiation, wind speed used for SWAT simulations are generated by weather data generator while precipitation and temperature data are historical observations from USDA. In order to gather the data needed for simulation, the study areas are overlaid with county boundaries of the United States to extracted the states and counties involved in each study area since the original USDA data are stored in different counties. (See Figure 4-2 Overlay watersheds on the map of counties)

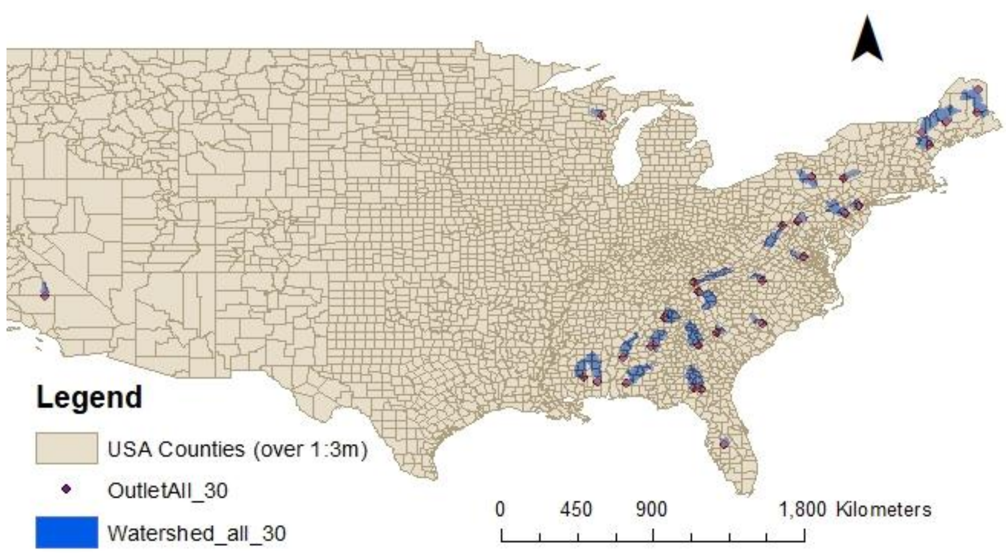

Figure 4-2 Overlay watersheds on the map of counties

There are 255 different counties involved in this study. In order to combine meteorological data into 30 files based on watersheds, a python script is developed for downloading historical rainfall and temperature data from USDA automatically. A list of the weather stations is created for each watershed. With the information of station numbers, station name, the latitude of the station, the longitude of the station, and elevation of the station, the lists are used when inputting the table of locations for SWAT simulations. Table 4-1 **Error! Reference source not found.**is a list of weather stations in TIOGA RIVER NEAR ERWINS, NY basin.

Table 4-1 List of weather stations in TIOGA RIVER NEAR ERWINS, NY basin.

ID	**NAME**	**LATITUDE (ºN)**	**LONGITUDE (ºW)**	**ELEVATION (Feet)**
1	C300023P	42.12	-77.23	299
2	C300028P	42.12	-77.22	373
3	C300448P	42.35	-77.35	341
4	C300816P	42.37	-77.10	336
5	C300817P	42.38	-77.12	415
6	C301173P	42.27	-77.62	352
7	C301603P	42.47	-77.50	445
8	C301787P	42.13	-77.07	348
9	C301792P	42.07	-77.05	500
10	C301794P	42.15	-77.10	287
11	C303722P	42.42	-77.57	503
12	C303983P	42.35	-77.70	404
13	C304772P	42.05	-77.13	317
14	C306831P	42.53	-77.30	591
15	C306833P	42.52	-77.27	439
16	C308498P	42.20	-77.33	494
17	C308594P	42.07	-77.48	521
18	C309125P	42.22	-77.42	323
19	C309229P	42.15	-77.57	661

4.2.2 SWAT Model Simulations

SWAT simulation is performed using SWAT 2012 Rev.664 after the weather information of a SWAT model is established. The period of interest is from January 1, 2001 to December 30, 2010 while the first two years are warm-up periods.

4.3 Model Calibration

4.3.1 Outflow Data Preparation

The unit of USGS historical daily averaged outflow from January 1, 2003, to December 31 are converted into cubic meters per second for calibration.

4.3.2 Model Calibration Using SWATShare

SWAT models are uploaded to SWATShare to perform the calibrations using the NSGAII algorithm. Table 4-2 is the parameters to be calibrated and their range.

On the SWATShare platform, the objective function is selected as the Nash-Sutcliffe model efficiency coefficient (NSE). NSE is defined as:

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_m^t - Q_0^t)^2}{\sum_{t=1}^{T}(Q_0^t - \overline{Q})^2} \qquad \text{Equation4.1}$$

where the Q_0 the mean of observed discharge, Q_m is modeled discharge, and Q_0^t is observed discharge at time t. SWATShare adopted the NSGA-II algorithm as the method for calibration. The process begins with a random parent population (Deb et al., 2002) as initial parameter sets, which are "generations" in SWATShare. Within each parameter set, parameter values are changed in the given range during the calibration process. This is called iterations in SWATShare. The NSE value is assessed using outflow data and the SWAT model output for each set of generation and iteration. For this study, 20 generations and 100 iterations are performed in each model. The calibrated models are stored for validation.

Table 4-2 Range of parameters for calibration

Parameter Name	Calibration method	Lower Bound	Upper Bound
CN2 Initial SCS runoff curve number for moisture condition II	%add	-0.25	0.25
GW_DELAY Groundwater delay [days]	Add	-10	10
ALPHA_BF Baseflow alpha factor [days]	Replace	0.01	1
GWQMN Threshold depth of water in the shallow aquifer required for return flow to occur [mm]	Replace	0.01	5000
GW_REVAP Groundwater "revap" coefficient	Replace	0.01	0.2
REVAPMN Threshold depth of water in the shallow aquifer for "revap" to occur [mm]	Replace	0.01	500
CH_N2 Manning's n value for main channel	Replace	0.01	0.15
CH_K2 Effective hydraulic conductivity [mm/hr]	Replace	5	100
CANMX Maximum canopy storage [mm]	Replace	0	25
ESCO Soil evaporation compensation factor	Replace	0.01	1
EPCO Plant uptake compensation factor	Replace	0.01	1
SFTMP Snowfall temperature [ºC]	Replace	0	5
SMTMP Snow melt base temperature [ºC]	Replace	-2	5
SMFMX Melt factor for snow on June 21 [mm H2O/ºC-day]	Replace	0	10
SMFMN Melt factor for snow on December 21 [mm H2O/ºC-day]	Replace	0	10
TIMP Snowpack temperature lag factor	Replace	0	1
SURLAG Surface runoff lag time [days]	Replace	0.05	24
SOL_AWC Available water capacity of the soil layer [mm H2O/mm Soil]	%add	-0.15	0.15
SOL_K Saturated hydraulic conductivity [mm/hr]	%add	-0.15	0.15

4.3.3 Model Calibration Using SWAT CUP

After simulated SWAT models are imported into SWAT CUP 2019 for calibration, SUFI-2 algorithm is selected for runoff calibration, and the objective function is set to the Nash-Sutcliffe model efficiency coefficient (NSE). Uncertainty in the Sequential Uncertainty Fitting (SUFI-2) algorithm is defined as the difference between simulated and observed variables (Rostamian et al. 2013). Instead of giving a parameter set, the results of SUFI-2 indicate the best range for each parameter and calculate the NSE value from one of the parameter sets in the best range. To get the best calibration result, SWAT CUP developer suggested a two-stage calibration (Abbaspour. K, 2014), dividing a two-thousand-simulations calibration into two sets of one-thousand-simulations calibration. During the first set of calibration, the range for parameters is the same as in Table 4-2. After finishing the first set of calibration, SWAT CUP suggests a new best range of all parameters and applies the range for the second set of one-thousand-simulations. Table 4-3 shows that one of the calibrated SWAT models has new best parameter ranges, which are different from the original setting.

Table 4-3 New Range for parameters after SWAT CUP calibration
(TIOGA RIVER NEAR ERWINS,NY)

Parameter Name	**Calibration method**	**Original Lower Bound**	**New Lower Bound**	**Original Upper Bound**	**New Lower Bound**
CN2	%add	-0.25	-0.29	0.25	0.07
GW_DELAY	Add	-10	-21.39	10	26.2
ALPHA_BF	Replace	0.01	0.20	1	0.73
GWQMN	Replace	0.01	-1206.64	5000	2931.44
GW_REVAP	Replace	0.01	0.06	0.2	0.15
REVAPMN	Replace	0.01	-128.13	500	290.65
CH_N2	Replace	0.01	0.06	0.15	0.17
CH_K2	Replace	5	44.92	100	124.77
CANMX	Replace	0	27.53	25	82.58
ESCO	Replace	0.01	0.41	1	1.22
EPCO	Replace	0.01	0.32	1	0.94
SFTMP	Replace	0	2.40	5	7.21
SMTMP	Replace	-2	-4.5	5	1.83
SMFMX	Replace	0	3.95	10	11.84
SMFMN	Replace	0	4.16	10	12.47
TIMP	Replace	0	0.41	1	1.23
SURLAG	Replace	0.05	4.80	24	17.6
SOL_AWC	%add	-0.15	-0.29	0.15	0.00
SOL_K	%add	-0.15	-0.24	0.15	0.02

4.4 Model Validation

USGA historical daily averaged outflow data from January 1, 2008, to December 30, 2010 are used for validation. The only exception was the USGS station 02074000. With data available only from January 2008 to October 30, 2009, the validation period of this watershed is set to the period that has data recorded.

Simulated outflow values are extracted, and the observed historical data are used for calculating NSE, R^2, KGE, and PBIAS.

NSE equation is shown in Equation 4.1, where Q_0 is the mean of observed discharge, Q_m is modeled discharge, and Q_0^t is observed discharge at time t.

R^2 is defined as:

$$R^2 = \frac{[\sum_i (Q_{m,i} - \overline{Q_m})(Q_{s,i} - \overline{Q_s})]^2}{\sum_i (Q_{m,i} - \overline{Q_m})^2 \sum_i (Q_{s,i} - \overline{Q_s})^2} \qquad \text{Equation 4.2}$$

Where Q is discharge and m and s stands for measured and simulated, and i is the i_{th} set of data.
KGE is defined as:

$$KGE = 1 - \sqrt{(\gamma - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \qquad \text{Equation 4.3}$$

Where $\alpha = \frac{\sigma_s}{\sigma_m}$, $\beta = \frac{\mu_s}{\mu_m}$, and γ is the linear regression coefficient between simulated and measured variable, μ_s and μ_m are means of simulated and measured data, σ_s and σ_m are the standard deviation of simulated and measured data. (Kling-Gupta efficiency, Gupta et al., 2009)
While KGE adopted NSE compositions into its components and addressed several shortcomings in NSE (Wouter J. M. Knoben et al., 2019), the method is gaining its popularity when evaluating model performance.
PBIAS is defined as:

$$PBIAS = 100 * \frac{\sum_{i=1}^{n} (Q_m - Q_s)_i}{\sum_{i=1}^{n} Q_{m,i}} \qquad \text{Equation4.4}$$

Where Q is discharge and m and s stands for measured and simulated, i is the i_{th} data.

To effectively calculate the objective function's value among thirty models, a python script is developed to help extracting simulated and observed outflow data. The script also helps to calculate NSE, KGE, R^2, PBIAS values.

5. RESULTS AND DISCUSSION

5.1 Introduction

This chapter presents the results and compares the calibrated parameter sets from different auto-calibration methods. To fully develop what affect the calibration results the most, features such as dominant land use, drainage density, ecoregion of the watershed, area of the watershed, the intensity of precipitation, and sensitivity of parameters in each basin are taken into consideration. The first part of this chapter presents the results of SWATShare and SWAT CUP calibrated models, explains the meaning of each parameter as well as how the parameters vary in different watersheds. The second part of this chapter examines the reliability of calibrated parameter sets. The third part of this chapter categorizes parameters using different geological, meteorological, or ecological classifications and visualizes the calibrated parameter distribution to identify correlations.

5.2 Calibrated Parameters

The comprehensive SWATShare and SWAT CUP calibrated parameters are listed in the appendix, APPENDIX
Table A-1 and Table A-2. This section discusses whether the values of parameters from SWATShare and SWAT CUP are in a physically meaningful range and quantify the difference between values from these two software.

5.2.1 Comparison of Parameters

GW_DELAY is the lag time for water to move past the underground to enter the shallow aquifer. For watersheds in the continental United States, this value can range from 1 to 100 days (Sawyer, L , 2010) The Value for this parameter range from 20 – 40 days for SWATShare, and between 0 – 445 days for SWAT CUP. Twenty-one out of thirty basins have values outside the 1 - 100 range from SWAT CUP.

ALPHA_BF is the baseflow recession constant. Its value ranges from 0.1 – 0.3 for watershed with slow response, while 0.9 -1.0 is the typical range for watersheds with rapid response. From SWATShare results, two of the watersheds in Alabama (station 02414715 and station 02425000.)

are in the rapid response range. However, these two watersheds are just on the higher end of the spectrum but not in the rapid response range from SWAT CUP.

GW_REVAP is the groundwater "revap" coefficient. With lower value, the evaporation and evapotranspiration is restricted. While all the GW_REVAP values calibrated by SWAT CUP are in the reasonable 0.02 - 0.2 range, two of the basins have values lower than the normal range from SWATShare. (station 01400500 in New Jersey and station 01054000 in New Hampshire)

GWQMN is the threshold depth of water in the shallow aquifer required for return flow to occur. With the higher value, groundwater is unlikely to flow to shallow aquifer. For SWATShare results, the values are between 79 - 4841mm, while the SWAT CUP values are between 0 - 5000mm. The zero values in SWAT CUP are unrealistic since it suggests that the groundwater in these basins can flow to the shallow aquifer without restriction.

CH_N2 is the manning's "n" value for the main channel. The values are all in a reasonable range for results from SWATShare and SWAT CUP. According to (Chow,1959), CH_N2 of a channel can be categorized into excavated or dredged and natural streams. (See Table 5-1) The calibrated values of CH_N2 suggest that most of the streams are natural streams, which are in accordance with the actual state of watersheds.

Table 5-1 Characteristics of channels and manning's n, part of (Chow,1959)

Characteristics of channel	N Range
Excavated or dredged	
Earth, straight of uniform	0.016-0.033
Earth, winding and sluggish	0.023-0.050
Not maintained, weeds and bush	0.040-0.140
Natural streams	
Few trees, stones or bush	0.025-0.065
Heavy timber and bush	0.050-0.150

CH_K2 is the effective hydraulic conductivity in the main channel. This value varies from 0 to 1000 in SWATShare results, and the value is zero for station 02317500 in Georgia, meaning the stream has a continuous groundwater discharge, which is unlikely to happen in an aquifer. Unlike

SWATShare results, the value varies from 4.24 to 172.16, with no extreme values from SWAT CUP. SWAT CUP thus provides a more reasonable hydraulic conductivity range.

ESCO is the soil evaporation compensation factor, and EPCO is the plant uptake compensation factor. With lower ESCO, a basin has the ability to extract more of the evaporative demand from lower levels. (Sharpley, et al., 1982). Thus, low ESCO should match with high EPCO in a watershed and vice versa. All the ESCO values from SWATShare and SWAT CUP are in the reasonable 0.01 – 1.0 range. While Station 02374250 in Alabama and station 02478500 in Mississippi have a minimum EPCO value of 0.01 from SWATShare, both watersheds have high ESCO values. From SWAT CUP, EPCO value of five basins (station 01526500 in New York, 02130980 in South Carolina, 03455000 in Tennessee, 01672500 Virginia, 01473500 in Pennsylvania) are large, but the results do not match with the ESCO results since the ESCO values in these watersheds are not small, which brings the SWAT CUP parameters to contradict with each other when examining the physical meaning of the values.

SFTMP is the snowfall temperature, while SMTMP is the snowmelt base temperature, these two values should be in the range from –5 ^{o}C to 5 ^{o}C. All of the values from SWATShare and SWAT CUP are in the reasonable range, and the results are similar.

SMFMX is the melt factor for snow on June 21, while SMFMN is the melt factor for snow on December 21. These two parameters are important for basins with significant snowfall. SMFMX in five of the watersheds from SWATShare and four from SWAT CUP are lower than 1.4mm H2O /day-°C. The results are reasonable since these basins have a larger urbanized area than others.

TIMP is the snowpack temperature lag factor. The typical Range for the factor is 0.01 – 1.0. The values of two basins from SWATShare are one (station 02478500 in Mississippi and station 01054000 in New Hampshire), meaning the effect of the snowpack temperature from yesterday affecting the snowpack temperature of the current day at these two watersheds are significant. While the rest of the values from SWATShare are in a typical range, some of the values from SWAT CUP are questionable. For example, the TIMP value of station 02294898 in Florida is one, which indicates the effect of the snowpack temperature is significant. However, it rarely snow in

Florida. Also, for stations 01066000, 01046500 in Maine, the TIMP values are zero, which is not reasonable since there is a significant amount of snowfall in Maine.

SURLAG is the surface runoff lag coefficient. In a large watershed, the time of concentration is usually greater than one day. SURLAG values are less than one in four of the basins from SWATShare. One possible reason is the watershed is small. However, three out of four watersheds mentioned above have a basin larger than 4000 square kilometers. With three watersheds (Station 01066000 in Maine, 01189500 in New Jersey, and 01614500 in Maryland) having SURLAG values less than one, SWAT CUP also have suspectable results.

5.2.2 Differences in SWATShare and SWAT CUP Parameters

Table 5-2 shows the Calibrated Parameter differences in %. The table is generated using the following formula:

$$\frac{\left|P_{share} - P_{cup}\right|}{[P_{s\max} - P_{s\min}]} \times 100\% \qquad \text{Equation 5.1}$$

Where P_{share} is the value of the SWATShare calibrated parameter, P_{cup} is the value of the SWAT CUP calibrated parameter, P_{smax} is the maximum calibrated value of SWATShare calibrated parameter, P_{smin} is the minimum calibrated value of SWATShare calibrated parameter. The percentage difference between 0 to 50% are highlighted in yellow; the difference between 50% to 100% are highlighted in dark blue, and difference larger than 100% are highlighted in red. The row: “Averaged Difference”, shows the percentage difference in each parameter between two calibrated methods. The difference in CH_K2 between two calibrated results is the smallest among all parameters, followed by ALPHA_BF, GWQMN. GW_DELAY has the most significant difference. The table shows that for most of the parameters, the difference between the two calibration methods is insignificant. Based on the result, one can conclude that the performance of SWATShare is comparable to SWAT CUP.

Table 5-2 Calibrated parameters differences in %.

Station number	CN2	GW_DELAY	ALPHA_BF	GWQMN	GW_REVAP	REVAPMN	CH_N2	CH_K2	CANMX	EPCO	ESCO	SFTMP	SMTMP	SMFMX	SMFMN	TIMP	SURLAG
02294898	Varies	151.9%	7.2%	34.3%	5.5%	34.9%	50.9%	7.2%	-	52.3%	31.6%	20.7%	8.1%	51.6%	62.1%	15.9%	100.0%
02374250	Varies	647.1%	7.5%	38.4%	46.2%	43.5%	34.7%	2.2%	-	0.5%	7.7%	76.1%	15.6%	84.5%	47.0%	39.8%	9.0%
02478500	Varies	570.4%	19.5%	15.3%	68.4%	61.0%	57.6%	0.4%	-	45.4%	94.8%	36.2%	31.8%	24.3%	17.9%	5.0%	54.5%
02414715	Varies	382.7%	29.9%	8.3%	78.7%	7.0%	4.1%	2.3%	-	3.3%	55.9%	104.2%	74.1%	99.2%	44.7%	8.5%	21.7%
02223000	Varies	835.6%	2.5%	8.3%	5.4%	27.1%	23.1%	7.3%	-	3.9%	16.5%	11.5%	26.0%	6.0%	35.7%	68.9%	2.0%
02196000	Varies	142.5%	67.5%	3.6%	2.4%	16.4%	8.2%	1.4%	-	44.4%	46.8%	96.6%	7.5%	43.5%	22.1%	6.6%	41.2%
02130980	Varies	28.5%	2.7%	7.4%	26.5%	61.7%	35.0%	93.9%	-	5.1%	29.5%	4.9%	14.9%	30.2%	53.4%	0.6%	41.2%
02387500	Varies	630.0%	8.1%	23.2%	3.3%	20.2%	13.0%	1.3%	-	16.0%	10.8%	36.6%	10.8%	39.6%	5.6%	40.4%	42.3%
01189500	Varies	103.6%	2.4%	14.3%	57.9%	100.0%	9.1%	1.8%	-	63.6%	13.2%	63.4%	5.4%	28.0%	88.7%	46.7%	42.9%
03455000	Varies	1564.8%	26.7%	3.0%	31.5%	16.3%	11.4%	0.4%	-	0.0%	12.5%	36.0%	12.3%	101.1%	40.8%	20.0%	18.1%
03528000	Varies	1789.7%	0.0%	7.2%	56.0%	9.1%	19.9%	1.1%	-	11.2%	9.8%	12.7%	62.7%	21.9%	22.2%	91.1%	37.1%
02074000	Varies	92.8%	4.4%	34.3%	35.8%	78.3%	50.4%	3.4%	-	5.8%	55.1%	16.6%	26.4%	43.5%	10.8%	12.0%	31.9%
01672500	Varies	780.4%	33.4%	2.2%	19.4%	50.8%	23.8%	7.0%	-	14.3%	9.8%	99.6%	21.4%	2.9%	100.0%	40.5%	12.5%
01608500	Varies	88.1%	7.6%	8.3%	0.4%	54.9%	9.6%	3.2%	-	51.5%	1.2%	31.3%	13.0%	54.6%	17.2%	23.2%	1.0%
01614500	Varies	103.2%	32.9%	0.7%	5.0%	21.5%	15.7%	8.3%	-	0.3%	10.7%	3.9%	21.1%	41.9%	53.9%	31.0%	82.5%
01473500	Varies	60.8%	47.5%	15.5%	11.8%	33.4%	12.1%	3.1%	-	52.4%	71.0%	18.1%	14.2%	102.4%	21.7%	6.0%	21.5%
01400500	Varies	13.0%	3.0%	10.0%	60.7%	34.1%	6.9%	2.1%	-	17.1%	9.4%	108.0%	49.5%	0.3%	19.5%	49.9%	9.3%
01426500	Varies	66.8%	14.8%	31.7%	58.5%	51.5%	1.4%	4.6%	-	30.1%	5.9%	17.8%	26.4%	10.4%	7.5%	39.7%	86.8%
01526500	Varies	98.2%	33.9%	6.7%	82.0%	17.7%	16.4%	3.5%	-	8.6%	17.5%	0.8%	27.4%	3.2%	19.1%	25.1%	39.0%
01066000	Varies	84.8%	1.5%	0.6%	43.7%	55.8%	3.6%	85.6%	-	16.2%	26.3%	1.4%	19.8%	56.1%	40.5%	3.2%	61.9%
01046500	Varies	99.5%	3.4%	12.0%	48.9%	13.3%	23.4%	1.4%	-	22.4%	17.3%	84.7%	23.5%	67.3%	8.6%	1.6%	50.8%
04067958	Varies	694.0%	3.1%	4.8%	48.9%	9.4%	11.4%	0.3%	-	29.5%	22.9%	13.3%	7.4%	45.6%	36.2%	9.5%	9.9%
01017000	Varies	55.9%	18.3%	95.0%	44.3%	42.1%	47.6%	3.6%	-	22.5%	7.4%	3.0%	60.8%	4.2%	51.8%	24.9%	7.0%
02425000	Varies	77.0%	19.1%	33.0%	4.4%	16.6%	50.1%	0.0%	-	6.3%	39.5%	33.2%	29.1%	66.7%	75.9%	24.8%	68.2%
02318500	Varies	116.3%	11.9%	5.9%	16.8%	1.4%	16.6%	0.4%	-	8.6%	7.4%	1.2%	34.6%	40.8%	9.4%	69.6%	22.3%
01030500	Varies	88.8%	7.9%	12.4%	25.7%	18.1%	2.3%	3.2%	-	31.1%	36.7%	3.5%	0.9%	4.3%	44.8%	2.3%	8.3%
01054000	Varies	135.8%	2.2%	14.4%	34.5%	2.5%	5.4%	0.2%	-	74.1%	58.3%	5.2%	8.3%	34.4%	6.0%	99.2%	3.6%
02317500	Varies	108.9%	2.5%	1.3%	54.8%	70.7%	72.6%	9.5%	-	43.1%	33.7%	22.9%	10.5%	9.2%	83.7%	20.6%	75.7%
02414500	Varies	165.3%	33.1%	77.2%	33.2%	24.9%	68.3%	0.4%	-	10.1%	42.3%	31.9%	23.5%	27.6%	22.0%	36.7%	28.7%
02473000	Varies	168.0%	22.5%	42.2%	17.6%	71.5%	63.0%	1.5%	-	28.0%	13.7%	21.0%	51.4%	24.3%	92.7%	44.2%	97.0%
Averaged Difference		331.5%	15.9%	19.1%	34.3%	35.5%	25.6%	8.7%		23.9%	27.2%	33.9%	24.6%	39.0%	38.7%	30.3%	37.6%

5.3 Evaluation of Model Performance

Section 5.2 reveals that there are some unreasonable parameter values among SWATShare and SWAT CUP calibrated models. This section reveals how the objective functions perform in these watersheds. The models with the objective function values greater than 0.3 are compared in Figure 5-1 and Figure 5-2, while the detailed values are listed in Table A-4 and Table A-5 in the appendix.

From the calibrated results, NSE values of nine SWATShare calibrated models are greater than 0.5, while only seven of SWAT CUP calibrated models greater than 0.5. Five of the models have larger than 0.5 NSE in both calibrated methods. Although most calibrated NSE are similar, some have significant differences in validated NSE. For example, watershed 01473500 has a 0.51 difference between the validated SWATShare and SWAT CUP results. Table A-4 and Table A-5 show that models with NSE greater than 0.5 are not necessarily a reliable model since the validated NSE should be considered as well. For example, while the calibration shows larger than 0.7 NSE, the validated NSE for watershed 02294898 in Florida are negative for both SWATShare and SWAT CUP. Among all SWATShare calibrated models, six models have negative NSE values. Also, there are six models among SWAT CUP calibrated models having negative NSE values. Five of the models show negative NSE value in both SWATShare and SWAT CUP validation. Ten of the SWATShare calibrated models have validated NSE values between 0 to 0.3. There are also ten SWAT CUP calibrated models having validated NSE between 0 to 0.3. Only five of the SWATShare calibrated models fall in the 0.3 to 0.5 NSE range, while seven of the SWAT CUP calibrated models are in this range.

Among thirty watersheds, NSE difference between SWATShare and SWAT CUP in 12 watersheds are less than 0.1, 19 of the watersheds are less than 0.2. The difference of KGE values between SWATShare and SWAT CUP results are even less, KGE difference in 13 are less than 0.1, 21 of the watersheds are less than 0.2.

As for the difference of R^2 values between SWATShare and SWAT CUP results, 19 watersheds are less than 0.1, 26 of the watersheds are less than 0.2.
Figure 5-1and Figure 5-2 show the comparison of objective function values that are larger than 0.3. Each dot in the figure represents the SWATShare (x-axis) and SWAT CUP (y-axis) objective

function value of a certain watershed. As shown in the figures, SWATShare and SWAT CUP have comparable results. Nonetheless, KGEs from SWATShare are higher in some watersheds. Overall, when looking at these statistical values, none of the calibrated models have an identical objective function results from SWAT CUP and SWATShare. However, over one-third of the models have a less than 0.1 difference in objective function results. Nearly two-thirds of the models have a less than 0.2 difference in objective function results.

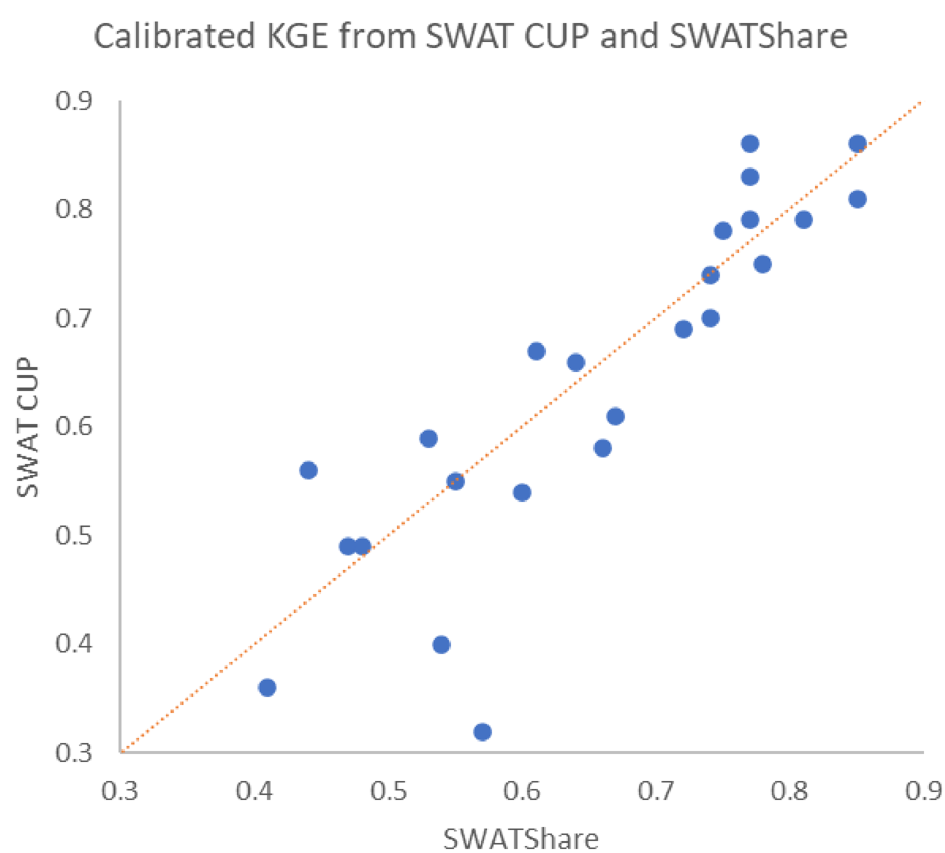

Figure 5-1 Comparison of calibrated KGE between SWAT CUP and SWATShare (>0.3)

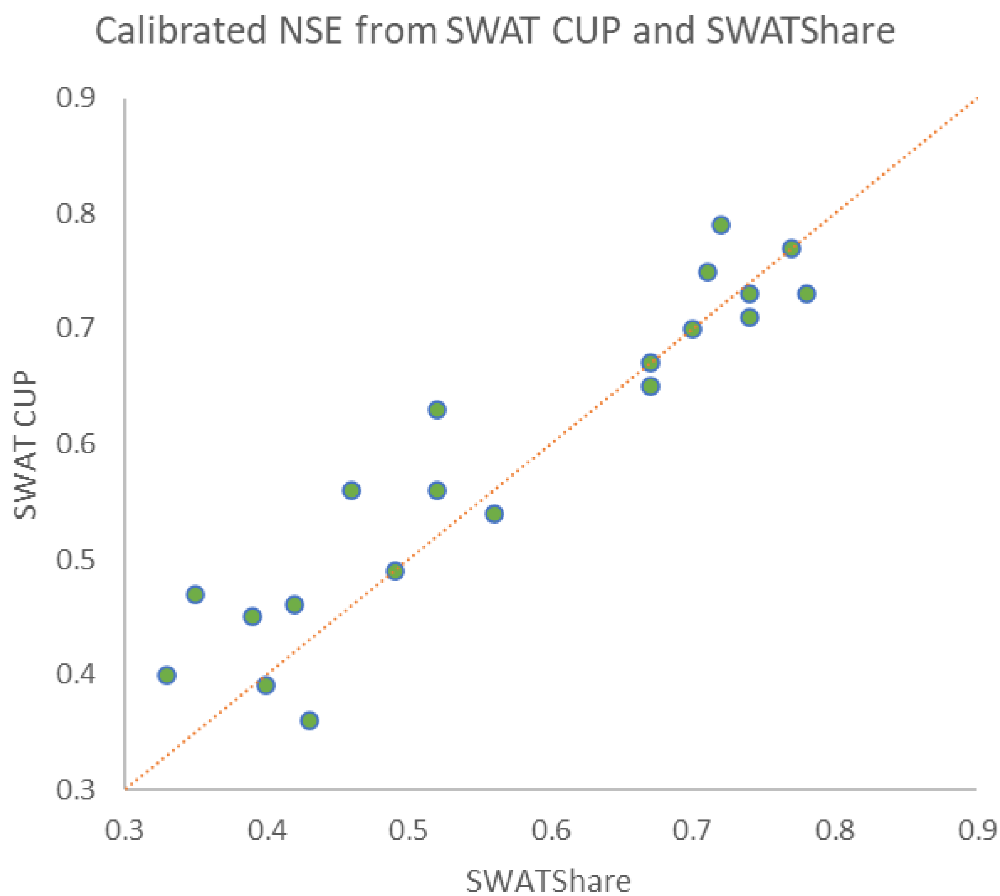

Figure 5-2 Comparison of calibrated NSE between SWAT CUP and SWATShare (>0.3)

5.4 Sensitivity Analysis Results

Figure 5-3 shows the top five sensitive parameters among all models. CANMX is identified as a sensitive parameter in 15 watersheds, while SURLAG and REVAPMN are sensitive in 11 watersheds. The complete result of sensitivity analysis is in

Table A-6. Compare the result from this study with the recommended parameters to be calibrated, GW_REVAP and SURLAG are two of the most commonly considered parameter. This proof the results from previous researches (Abbaspour K.C. 2004, 2014, 2016, Eckhardt K and J.G. Arnold, 2013)

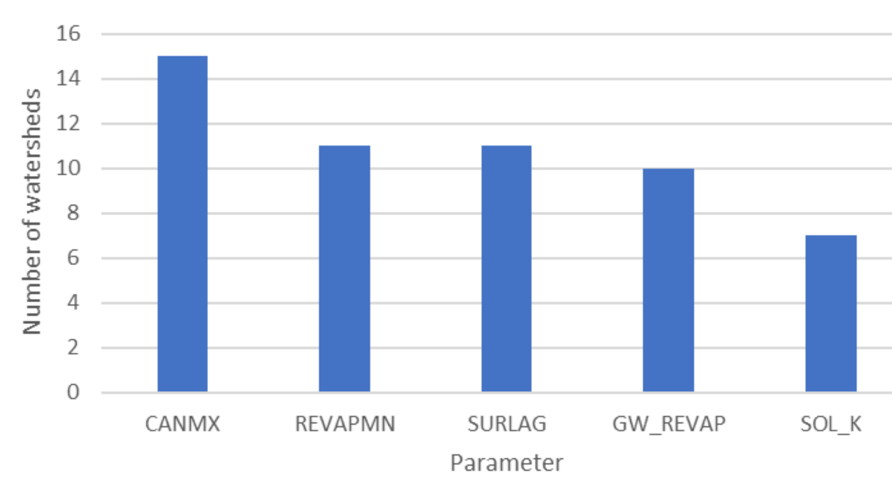

Figure 5-3 Top five sensitive parameters

5.5 Correlations Between Parameters

Previous sections compare only the reliability of each parameter value and the overall calibrated model performance of individual watershed. In this section, watershed features such as climate zone distribution, ecological region, hydrological features, meteorological distribution of watersheds are extracted and classified to answer the question that, what characteristics of basins affect the calibration the most? In this section, the features mentioned above are visualized based on their correlations.

Besides parameters, some watershed characteristics can also be analyzed. For example, basins are categorized into four different land-use types: Water, Medium Residential, Forest, Agricultural for feature correlation analysis. Dominant land use is considered as a feature for analysis since it affects infiltration, transpiration, and impervious area in a basin. These properties usually alter the timing and volume of baseflows.

Also, topographical features such as Reach length, averaged slope of the river, drainage density of watershed are extracted for feature correlation analysis since catchment geology is a primary control on the baseflow-generating process. (Bloomfield et al., 2019) These properties can be extracted from DEMs for the study areas.

Historical peak outflow rate, minimum outflow rate, and outflow standard deviation of study rivers are considered when performing correlation analysis. These features help to determine whether the extreme weather will affect the parameters calibration process or not.

To include other possible features that will affect the parameters calibration, climate zone, and ecoregions of watersheds are taken into consideration. Ecoregion is used for analysis since it is a pattern of ecosystems associated with characteristic combinations of soil and landform that characterized that region. (Omernik,2004). When categorizing watersheds based on climate zones, fifteen watersheds are located in the Humid continental region, fourteen of the watersheds are in the Humid subtropical region, and one is in the Mediterranean region. When considering ecoregions, all thirty watersheds are distributed in ten different ecoregions.

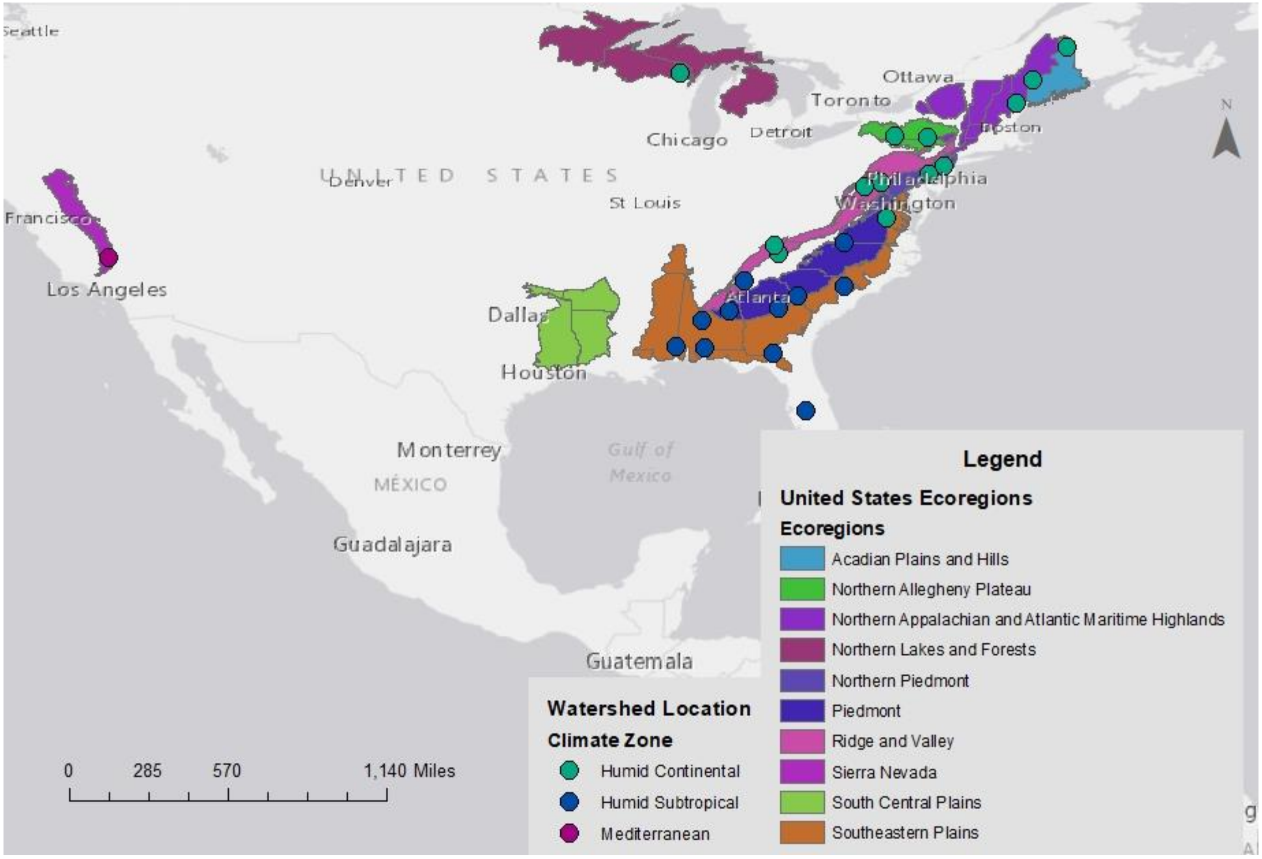

Figure 5-4 Ecoregions of the study watersheds

To see if there is any regional difference in calibrated parameters, statistics of parameter values are calculated based on weather zones and ecoregions. Figure 5-5 and Figure 5-6 present NSE and KGE Values in different climate zones. The graphs show that the NSE values in the Humid Subtropical region are lower than the values in the Humid Continental region from SWATShare, while there is no significant difference between the Humid Subtropical and the Humid continental region from SWAT CUP. Both software do not perform well in the Mediterranean region, but the low performance in this climate zone is inconclusive since there is only one watershed been examined in this region.

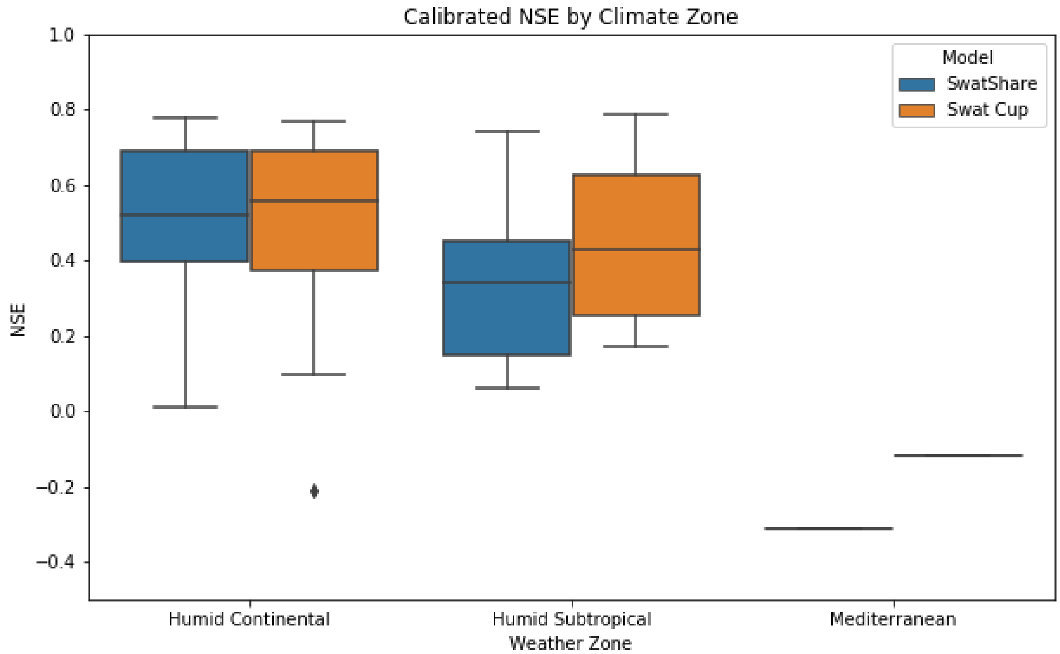

Figure 5-5 Comparison of NSE values in different climate zones

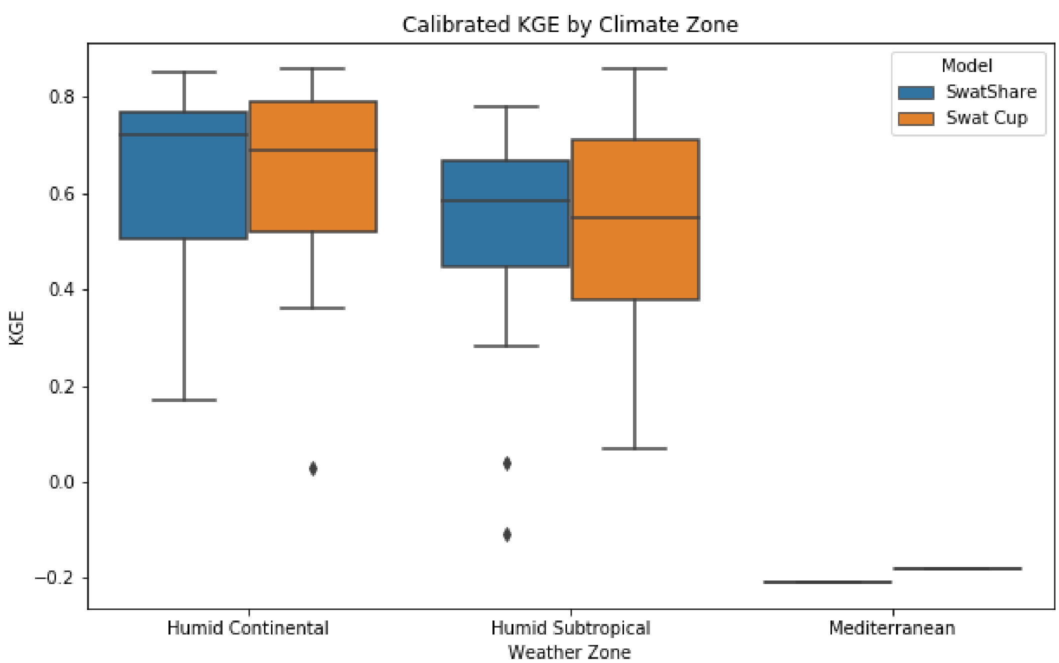

Figure 5-6 Comparison of KGE values in different climate zones

In Figure 5-7, averaged TIMP values in different climate zones are presented. Other than the Mediterranean region, SWATShare calibrated models have higher TIMP in both Humid Subtropical and Humid Continental region than SWAT CUP calibrated models. TIMP values in both SWATShare and SWAT CUP are larger in the Humid subtropical region than in the Humid continental region.

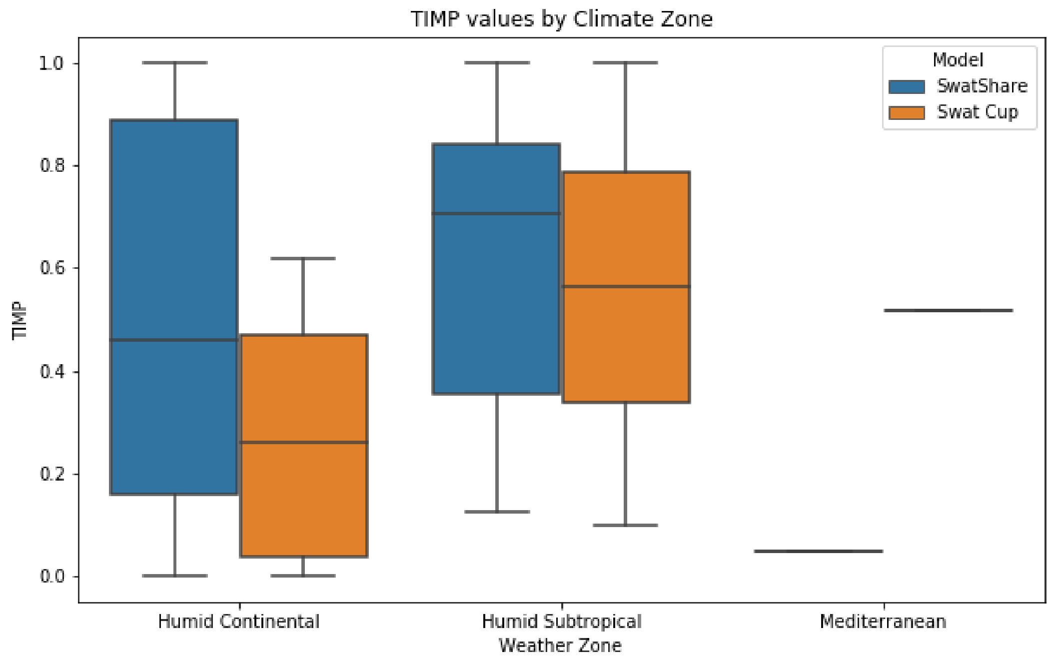

Figure 5-7 TIMP Values in different climate zones.

In Figure 5-8, averaged GW_DELAY days in different ecoregions are shown. The red line represents SWATShare results. In SWATShare calibrated models, the averaged GW_DELAY days do not change much in different ecoregions. While in SWAT CUP calibrated models, the averaged GW_DELAY varies. Some of the GW_DELAY values calibrated by SWAT CUP are even in a physically unrealistic range. (>100)

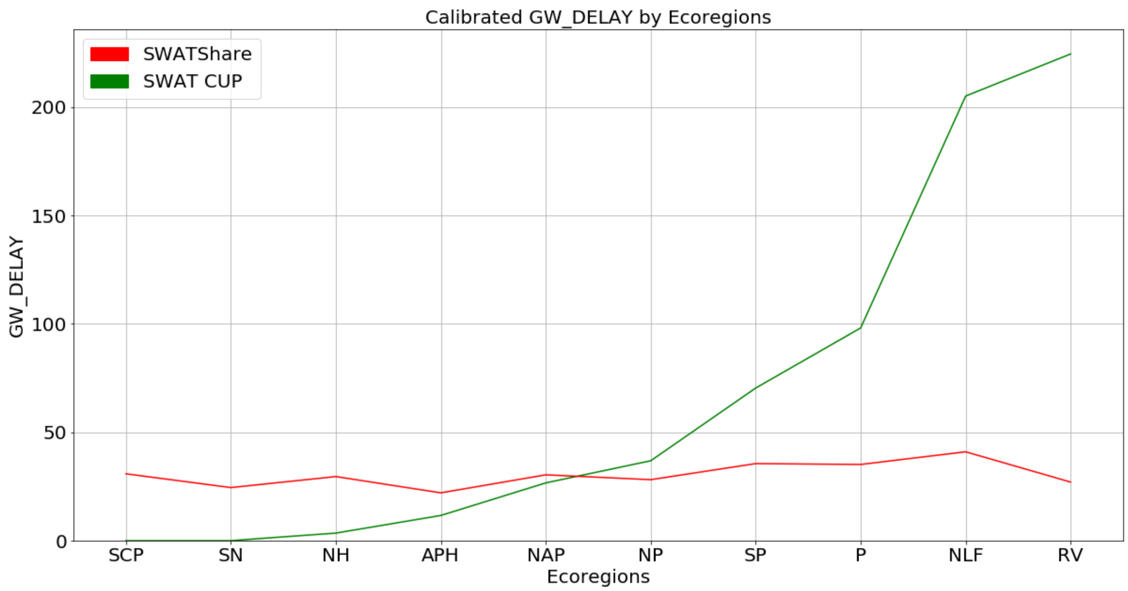

Figure 5-8 Averaged GW_DELAY days in different ecoregions

With the red line represents SWATShare results, Figure 5-9 shows that the averaged CH_N2 in an ecoregion are similar from SWATShare and SWAT CUP. The results are thus comparable.

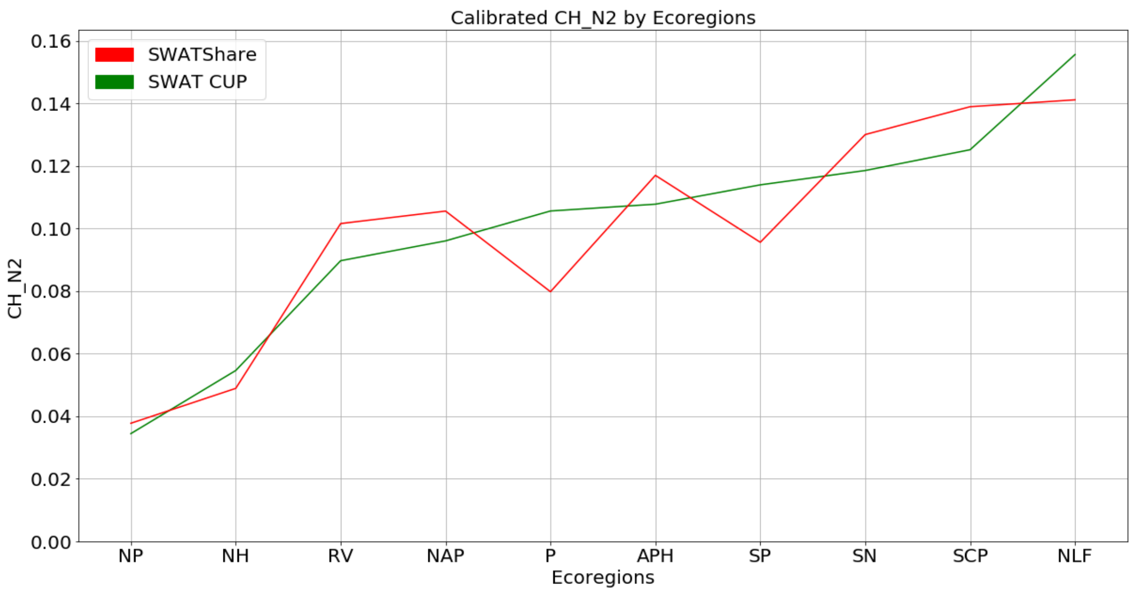

Figure 5-9 Averaged CH_N2 in different ecoregions.

The results from Figure 5-10 SURLAG in different ecoregionsand Figure 5-11 show that besides the Ecoregion: Southern Coastal Plain (SCP), parameter values calibrated by SWATShare are similar to parameter values calibrated by SWAT CUP in most of the ecoregions

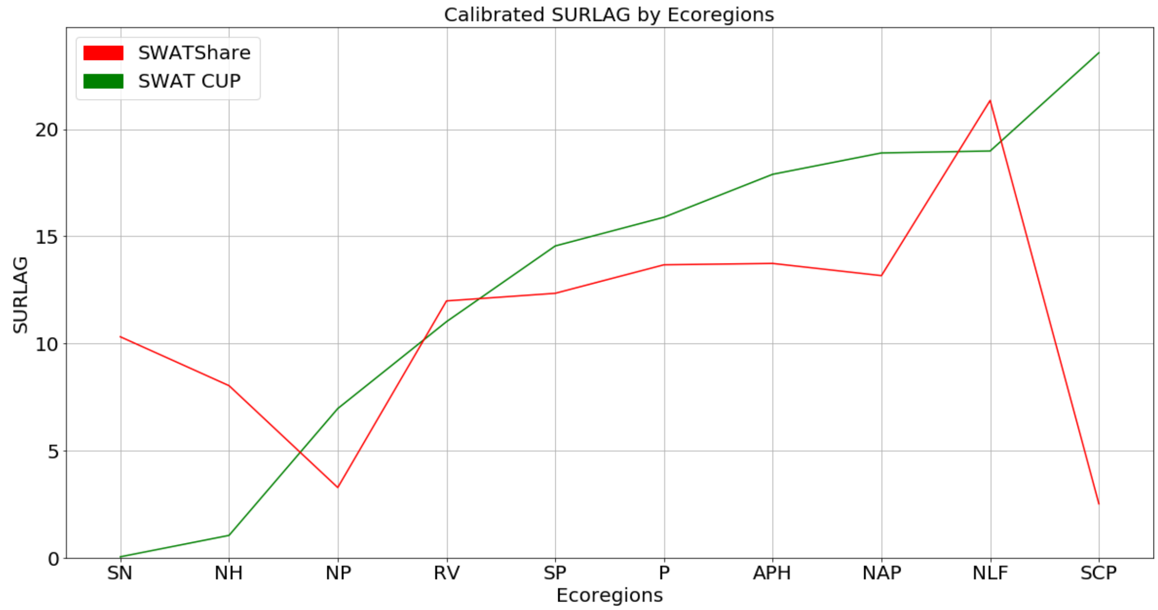

Figure 5-10 SURLAG in different ecoregions

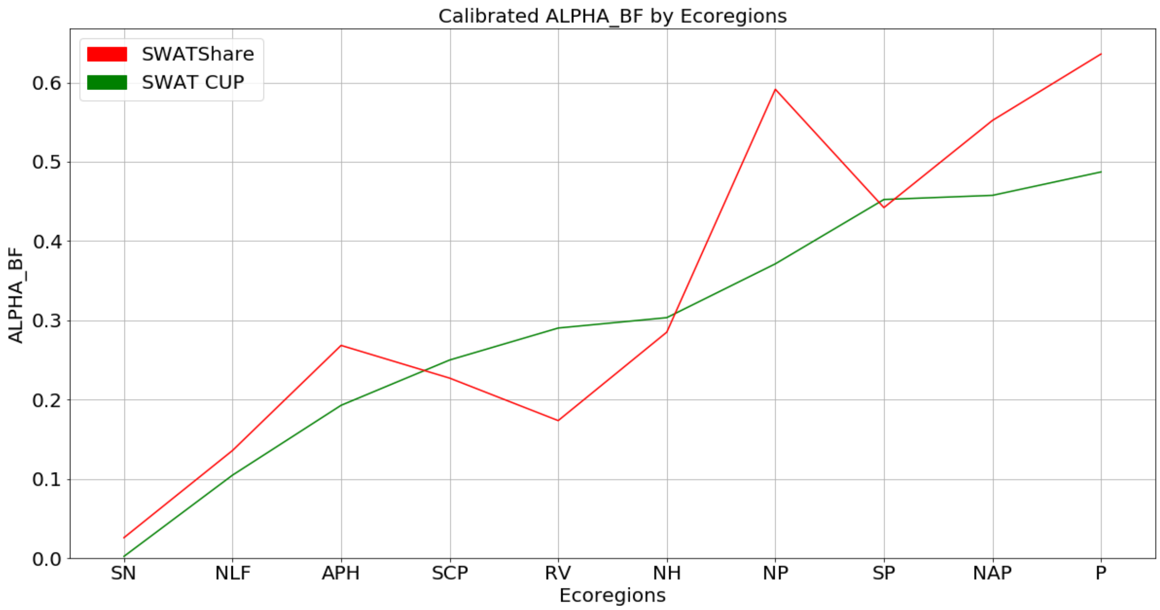

Figure 5-11 ALPHA_BF in different ecoregions

When considering using objective functions to evaluate the performance of calibrated models, the Kling–Gupta efficiency (KGE; Gupta et al., 2009) is also a good indicator for evaluating model performance. KGE adopted NSE compositions into its components and addressed several shortcomings in NSE (Wouter J. M. Knoben et al., 2019), KGE is thus increasingly adopted for model evaluation. In Figure 5-12 the blue boxes represent SWATShare results. Most of the KGE within an ecoregion from SWATShare and SWAT CUP are similar. However, in the Ecoregion: Southern Coastal Plain (SCP) calibrated KGE values show some difference between SWATShare and SWAT CUP. In ecoregions: Northern Piedmont (NP) and Northern Allegheny Plateau (NAP), both SWATShare and SWAT CUP performance are well and provide almost identical values. The above results confirm that SWATShare has the ability to provide reliable calibrations. Also, in some of the ecoregions, the best parameter sets from SWATShare are in a more physically meaningful range.

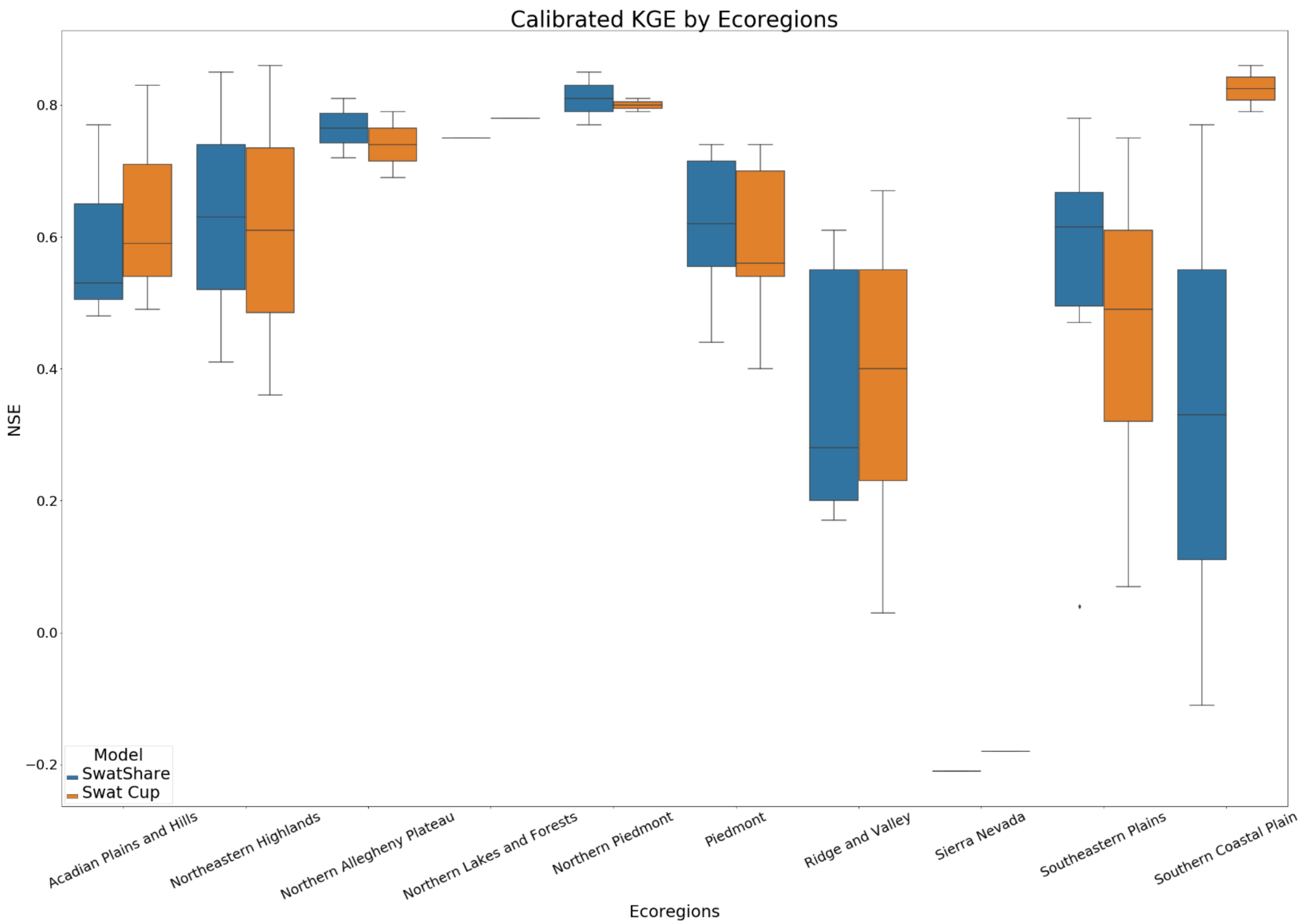

Figure 5-12 KGE values in different ecoregions

In Figure 5-13, averaged NSE values in different ecoregions are shown. The red line represents SWATShare results. Most of the averaged NSE within an ecoregion from SWATShare and SWAT CUP calibrated models are similar. However, in ecoregion: Southern Coastal Plain (SCP) calibrated NSE value from SWATShare is much lower than the SWAT CUP, and in ecoregions: Northern Piedmont (NP) and Northern Allegheny Plateau (NAP), both SWATShare and SWAT CUP perform well and provide almost identical values.

With some patterns from the visualized results, it is still hard to conclude that climate zones and ecoregions are useful features to categorize values of parameters and performance. Although two of the climate zones each covered 14 and 15 watersheds, the number of watersheds studied is still insignificant. Nevertheless, when looking at ecoregions, six watersheds are explored in each ecoregion at most. More watersheds need to be involved when determining whether the categorized results are reliable.

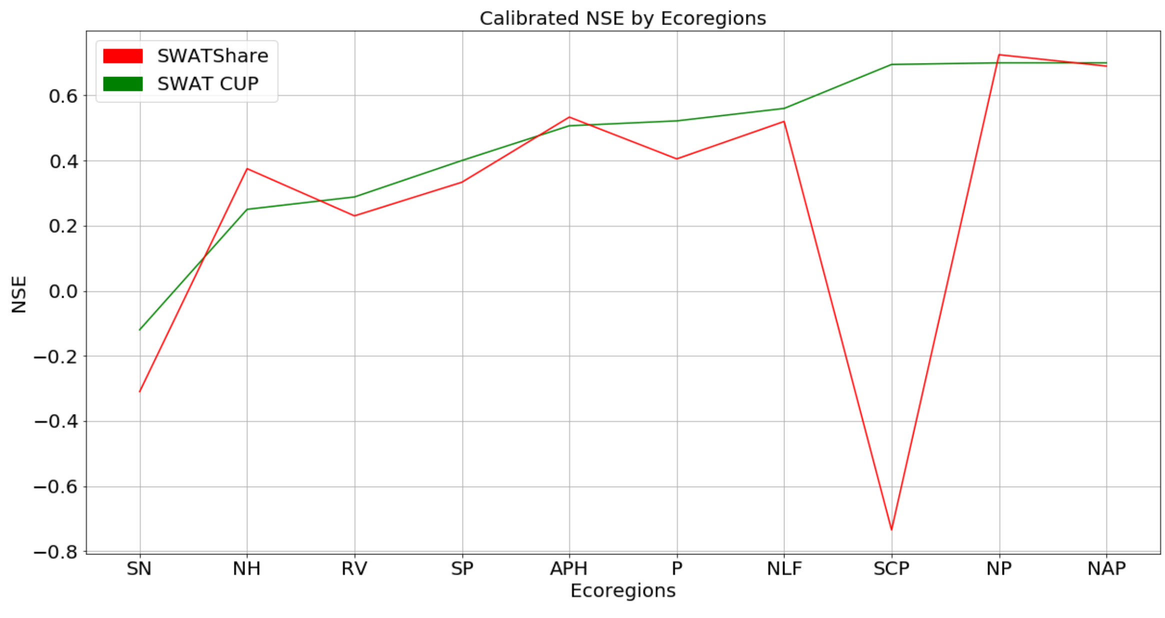

Figure 5-13 Averaged NSE in different ecoregions

To identify the correlation between features and parameters, the Pearson correlation coefficient (PCC) is considered. The coefficients are used in comparing the correlation between two features or between two parameters. With a value between -1 and +1. Equation 5.2 is used to calculate the correlation in a population,

$$PCC = \rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} \qquad \text{Equation 5.2}$$

Where COV is the covariance σ_X is the standard deviation of series X, σ_Y is the standard deviation of series Y. Pearson correlation matrix of SWATShare calibrated results is presented in Figure 5-14, while the Pearson correlation matrix of SWAT CUP calibrated results is shown in Figure 5-15. In these two figures, the number in each cell represents the correlation between the two components. The cells are filled with colors from green to red. The higher the coefficient is, the darker red the cell is.

To identify the strength of correlations, the coefficients were categorized into five categories. (1) Perfect: If the absolute coefficient value is near 1. (2) strong correlation: If the absolute coefficient value lies between 0.5 and 1; (3) Medium correlation: If the absolute coefficient value lies between 0.3 and 0.5; (4) Small correlation: If the absolute coefficient value lies below 0.3; (5) No correlation: If the absolute coefficient value is zero. In the following paragraphs, the component sets which have a medium or strong correlation are discussed.

In Pearson correlation matrix of SWATShare calibrated results, for relations between parameters, GW_DELAY and TIMP have a 0.54 coefficient, which is considered a strong correlation. ESCO and GWQMN have a strong negative correlation with a -0.64 coefficient. TIMP and REVAPMN also have a strong negative correlation with a -0.51 coefficient. For relations between parameter and feature, the Weather zone and SMFMX have a strong correlation with 0.53 PCC. Ecoregion and SMFMX also have a strong correlation with 0.53 PCC.

In Pearson correlation matrix of SWAT CUP calibrated results, for relations between parameters, SURLAG and CH_N2 have a 0.5 strong correlation. There is no other strong correlation between features and parameters or between parameters. However, the correlation matrix shows several medium correlations between components.

Comparing two coefficient matrices of calibrated results, in both SWATShare and SWAT CUP calibrated model correlation coefficient matrices, CH_N2 and ALPHA_BF have a medium correlation. SMFMX and GWQMN, the length of reach and GWDELAY, reach slope and

REVAPMN, climate zone and GWQMN also have a medium correlation. Both components set: SMFMN and GW_DEALY, SMFMN, and ALPHA_BF have a medium correlation. In SWATShare calibrated models, the medium correlations are positive, while in SWAT CUP calibrated models, the correlations are negative. The medium correlations of these two components set are thus doubtful since the results from SWAT CUP and SWATShare have opposite correlations (positive and negative). Unlike the relation mentioned above, SFTMP has a medium correlation with NSE value in both matrices.

Component sets reach length and GW_DELAY, CH_N2 and ALPHA_BF, climate zone and GWQMN, SFTMP and NSE have a medium correlation in both SWATShare and SWAT CUP calibrated models and the correlation coefficient difference are less than 0.1. From Figure 5-16, parameters including GW_DELAY, ALPHA_BF, GWQMN, CH_N2, CH_K2, ESCO, EPCO, SFTMP, SMTMP, TIMP, and KGE have medium to high correlations between SWATShare and SWAT CUP calibrated models. This again confirmed that the calibration results from SWATShare are comparable to the results from SWAT CUP.

The correlation coefficient provides quantified value for interpreting relationships between hydrological features and model parameters. However, assuming the correlations are linear when calculating the coefficient might lead to biases when interpreting the results. Also, the population size of this study (30 watersheds) is not large enough for a conclusive argument.

Most of the coefficients are different when comparing SWATShare and SWAT CUP results. For the component sets that SWATShare results agree with SWAT CUP results, other calibrated models for validation are needed to determine whether these component sets have medium or strong correlations. Overall, correlation coefficient analysis provides an outline of how parameter varies with other parameters or features in SWATShare and SWAT CUP. The correlation values could help modelers to determine which parameters to change based on existing physical features of a study watershed. Researchers could also consider pairing highly correlated component sets when conducting calibration to enhance performance.

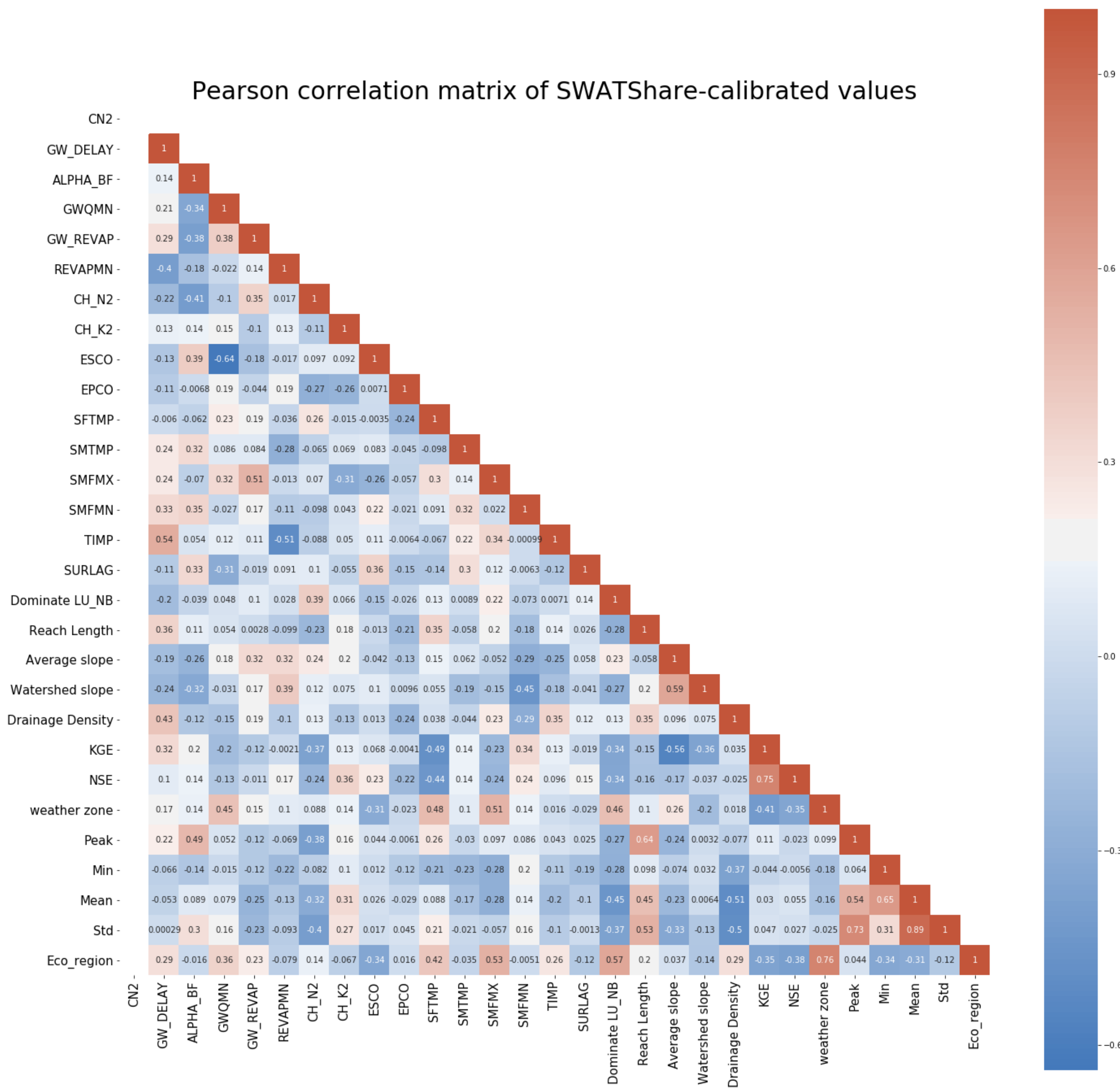

Figure 5-14 Pearson correlation matrix of SWATShare calibrated results

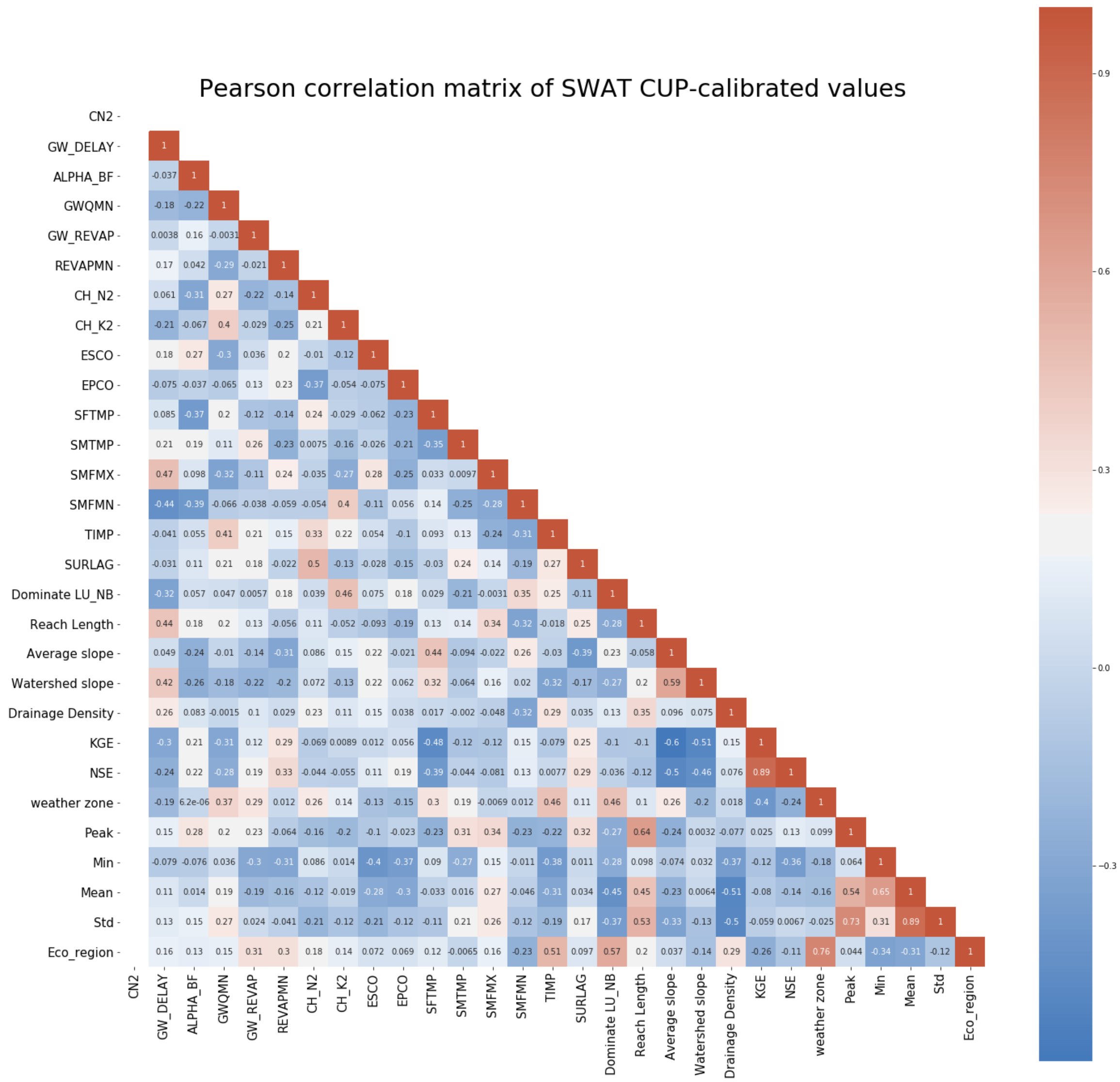

Figure 5-15 Pearson correlation matrix of SWAT CUP calibrated results

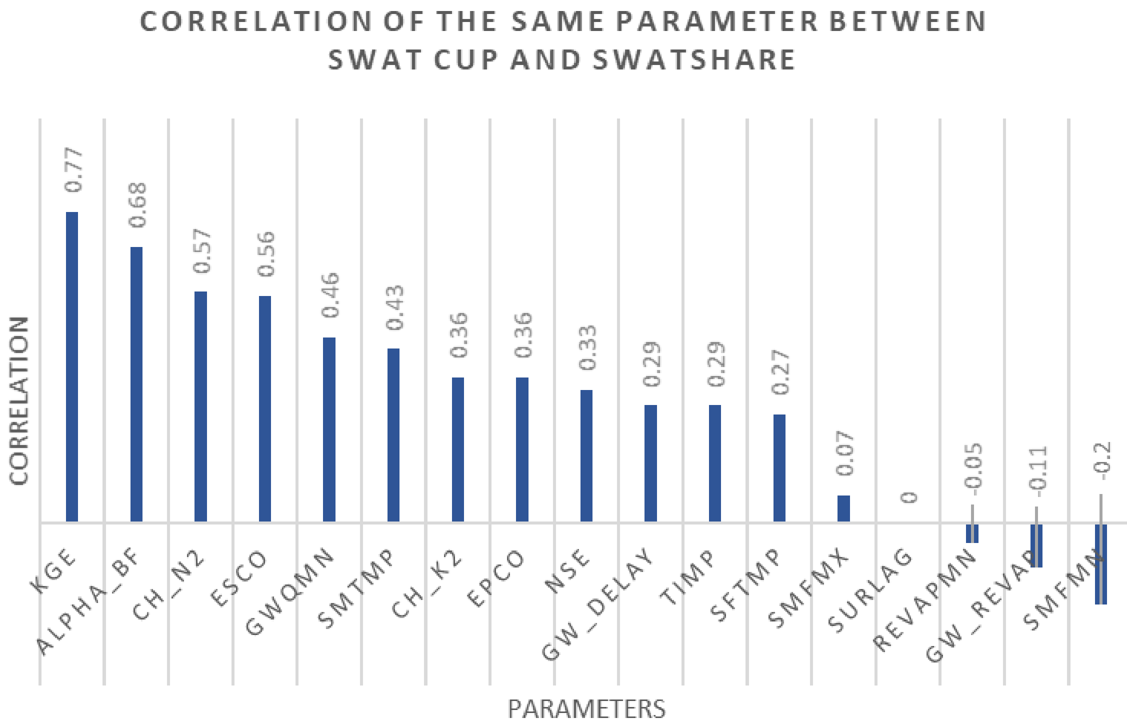

Figure 5-16 Correlation of the same parameter between SWAT CUP and SWATShare

5.6 Effect of New Parameter Range

In the results of the SWAT CUP and SWATShare calibrated models, some of the watersheds have similar NSE values. However, the parameter sets do not agree with each other when considering models calibrated by different algorithms. When looking at the SWAT CUP calibrated models, some parameters such as groundwater delay days, maximum canopy storage are not in a reasonable range. Also, even though the validated NSE value is high, whether the calibrated model is reliable when predicting future events is questionable. This section aims to answer these questions: Will satisfactory NSE value still exist after fixing the parameter range in SWAT CUP to a more realistic scenario? And for the watersheds that have low-performance SWAT CUP calibrated model but high-performance SWATShare calibrated model, will the results improve when changing the SWAT CUP parameter range to match the calibrated SWATShare parameter range? Also, for the watershed that has a low-performance SWATShare but a high-performance SWAT CUP results, will the results improve when changing the SWATShare parameter range to match the parameter range that SWAT CUP suggests?

Watershed with Station number 01066000 in Maine has satisfactory calibrated objective values from both SWAT CUP and SWATShare. The SWAT CUP calibrated model has a lower NSE value (0.34) when validated compare to the SWATShare calibrated model, which gives a satisfactory NSE (0.62). There are some unrealistic parameter values in the best-fit parameter set of the SWAT CUP calibrated model. For example, the groundwater delay days is 6.97, which is relatively low for a watershed of this size. Also, the snow-pack temperature lag factor is zero, which should be between 0.01 to 1 and the surface runoff days is 0.5, which should be greater than one. To examine whether the satisfactory NSE value still exist after fixing the parameter range in SWAT CUP to a more realistic scenario, the range of parameters for calibration is changed according to the calibrated parameter set from SWATShare. The new range is listed in Table 5-3. The objective function values of the new calibrated model are equally good as the original one. With KGE= 0.86, NSE=0.68, R^2=0.73. Also, the parameter values in the best-fit parameter set are in a reasonable range. However, the validation shows that the new calibrated model performs worse than the first calibrated model, with negative NSE and KGE values.

Table 5-3 New range of parameters for calibration

Parameter Name	Calibration method	Lower Bound	Upper Bound
CN2 Initial SCS runoff curve number for moisture condition II	%add	-0.25	0.25
GW_DELAY Groundwater delay [days]	Replace	0.5	50
ALPHA_BF Baseflow alpha factor [days]	Replace	0.01	1
GWQMN Threshold depth of water in the shallow aquifer required for return flow to occur [mm]	Replace	0.01	5000
GW_REVAP Groundwater "revap" coefficient	Replace	0.01	0.2
REVAPMN Threshold depth of water in the shallow aquifer for "revap" to occur [mm]	Replace	0.01	500
CH_N2 Manning's n value for main channel	Replace	0.01	0.15
CH_K2 Effective hydraulic conductivity [mm/hr]	Replace	5	100
CANMX Maximum canopy storage [mm]	Replace	0.01	100
ESCO Soil evaporation compensation factor	Replace	0.01	1
EPCO Plant uptake compensation factor	Replace	0.01	1
SFTMP Snowfall temperature [ºC]	Replace	0	5
SMTMP Snow melt base temperature [ºC]	Replace	-2	5
SMFMX Melt factor for snow on June 21 [mm H2O/ºC-day]	Replace	0	10
SMFMN Melt factor for snow on December 21 [mm H2O/ºC-day]	Replace	0	10
TIMP Snowpack temperature lag factor	Replace	0	1
SURLAG Surface runoff lag time [days]	Replace	0.05	24
SOL_AWC Available water capacity of the soil layer [mm H2O/mm Soil]	%add	-0.15	0.15
SOL_K Saturated hydraulic conductivity [mm/hr]	%add	-0.15	0.15

Watershed with Station number 02473000 in Mississippi also has similar calibrated objective values from both NSGA-II and SUFI-2 algorithms. The SWAT CUP calibrated model has a lower NSE value (0.17) when validated compare to the SWATShare calibrated model, which gives an NSE value close to calibrated NSE value (0.41). There are some unrealistic parameter values in the best-fit parameter set of the SWAT CUP calibrated model. For example, the groundwater delay days is zero, which should be in the range between 10-100. Also, the maximum canopy should be greater than zero, especially in a forest-dominated watershed. The ranges of parameters for calibration are changed to realistic ranges, and a new set of calibration is performed using SWAT CUP. The objective function values of the new calibrated model are slightly lower than the original model. With KGE= 0.52, NSE=0.40, R^2=0.47. However, the validation shows that the new calibrated model performs better than the first calibrated model. With NSE= 0.40, KGE=0.7, and R^2=0.52, the objective function values of new calibrated models are similar to the SWATShare calibrated result.

Watershed with Station number 02318500 in Georgia has good calibrated objective values from both SWAT CUP and SWATShare. The validations also confirmed good performance in both models. However, there are some unrealistic parameter values in the best-fit parameter set. The groundwater delay day from SWAT CUP is zero, while the result from SWATShare is 27.51 days. Also, maximum canopy storage is zero millimeters, which should be low but greater than zero in an agriculture dominated watershed. To see whether the results will be improved when changing the SWAT CUP parameter range to match the calibrated SWATShare parameter, the ranges of parameters for calibration are changed to realistic ranges, and a new set of calibration is performed using SWAT CUP. The objective function values of the new calibrated model are slightly higher than the original model. With KGE= 0.79, NSE=0.78, R^2=0.85. The validation shows that the new calibrated model performs equally well as the first calibrated model. The objective function values of new calibrated models are similar to the SWATShare calibrated result, and the new calibrated groundwater delay days are close to the SWATShare calibrated value.

The initial parameter range used for SWAT CUP calibration could lead to a good result. However, the parameter values of the calibrated model might not be presenting a real physical condition. Watershed with Station number 02473000 in Mississippi shows that the inaccurate parameter values might lead to lower objective function values for validation. The objective function values can be improved by simply setting the range of parameter values to match the SWATShare calibrated values. Watershed with Station number 02318500 in Georgia shows that constraining the parameter to a reasonable range for a model with good performance will not decrease the objective values of the model. Moreover, the objective values are improved in this case. Changing the parameter values according to SWATShare calibrated results is not a panacea for all unsatisfactory models calibrated by SWAT CUP. The new calibrated model of the watershed with Station number 01066000 in Maine is as good as the original calibrated model in terms of objective function values in calibration. However, the validation result of the new calibrated model is worse than the original calibrated model. One possible reason is, although the surface runoff lag days of the new calibrated model is in a reasonable range, it is still on the lower end compare to the values in the other watersheds.

Watershed with Station number 01473500 in Pennsylvania has satisfactory calibrated objective values from both NSGA-II and SUFI-2 algorithms. However, the validation of the SWATShare calibrated model shows low objective function values (NSE=0.07). The only unrealistic parameter value in the best-fit parameter set of the SWATShare calibrated model is the low surface runoff delay days (0.43). With new suggested ranges of parameter values that exist in SWAT CUP calibrated results. The objective function values of the new calibrated SWATShare results are significantly improved to a satisfactory range. With KGE= 0.76, NSE=0.59, R^2=0.64. The result implies that, by combining SWAT CUP results in SWATShare calibration process, the performance of SWATShare could be improved.

Compared to SWATShare, SWAT CUP tends to inaccurately calibrates parameter values to an unrealistic range using default boundary values. In most cases, the objective function values could be improved after specifying the parameters to a realistic range. For those watersheds which have similar satisfactory calibrated objective values from both SWAT CUP and SWATShare, constraining the parameter to a reasonable range could generate a new calibrated model that performs as good as the original one. The phenomenon is also known as the equifinality of hydrological models. It is subjective to decide which model is better when dealing with the equifinality of models. However, using the approach to constrain parameter values to a realistic range can exclude some statistically satisfactory but physically meaningless models.

6. SUMMARY AND CONCLUSION

While SWAT model can be used to simulate both the quantity and quality of surface water, surface run-off simulation is the focus of this study. Objective function values are presented to evaluate the calibrated model performance of both SWAT CUP and SWATShare in 30 basins. When looking at only objective function values, SWAT CUP and SWATShare show no significant difference in most of the watersheds. NSE difference between SWATShare and SWAT CUP in twelve watersheds are less than 0.1, while the difference in nineteen of the watersheds are less than 0.2. The reliability of calibrated models depends not only on objective function values but also on calibrated parameter values. SWATShare and SWAT CUP share the same initial range of parameters for calibration. However, to obtain optimal calibration results, the SWAT CUP parameter range was modified to the new suggested range after performing the first set of the calibration. The process of modifying the calibration range can help the model to reach better objective function values but lead to unrealistic parameter values.

Although the objective function values are similar in most of the watersheds, some of the calibrated parameter values have a significant difference. The percentage difference of parameter values ranges from 8.69% (Effective hydraulic conductivity) to 331.48% (Groundwater delay). Based on the results, SWATShare and SWAT CUP can both perform satisfactory calibrations, but the same parameter of one watershed in different calibrated models can have quite the opposite values. Although the SWAT CUP procedure suggests that besides the best parameters set, the effective range of parameters should also be considered, some of the SWAT CUP calibrated parameters are still out of the best range envelope. These results are due to the equifinality of different approaches when calibrating SWAT models; two inconsistent parameter sets could yield equally acceptable results. The best parameter sets in SWATShare fall in a more reasonable range when comparing which auto-calibration tool can provide a more realistic calibrated model. The purpose of calibration is to ensure a hydrological model can conduct satisfactory simulations when forecasting future events. Unrealistic parameter values in a model can be either irrelevant to the result or significantly decrease the reliability of the model. If the unrealistic parameters are sensitive in calibrated SWAT models, the unrealistic parameters would lead to unsatisfactory objective function values in validation.

Watershed characteristics are extracted and analyzed to determine whether the performance of calibration and parameters have a linear correlation to geographical, topological, or climate differences. Some of the parameters or features of the watershed have strong correlations. As for SWATShare calibrated results, groundwater delay, and Snowpack temperature lag factor; Climate zone of a watershed and melt factor for snow; Ecoregion of a watershed and melt factor for snow all have strong correlations. However, from SWAT CUP calibrated results, only surface run-off lag coefficient and manning's n of channels have a strong correlation. Some of the parameters or features have a medium correlation in both SWATShare and SWAT CUP calibrated models, including groundwater delay and reach length; manning's n of channels and baseflow recession constant; climate zone of a watershed and threshold depth of water in the shallow aquifer required for return flow to occur; melt factor for snow and NSE value. These correlations can help to choose the desired parameters to calibrate based on the existing physical features of a watershed. The performance of calibration could also be enhanced by pairing highly correlated component sets.

The correlation coefficient helps to identify relationships between hydrological features and model parameters. When performing correlation analysis, features and parameter values are assumed to have a linear correlation. However, the correlations are not necessarily linear. Also, with a small population size, which is 30 watersheds, results are easily biased. Thus, besides statistical figures, visualization is used to analyze results. When categorizing results by Ecoregions, some trends are revealed. Based on the results, SWATShare has the ability to provide reliable calibrations. Also, in some of the ecoregions, the best parameter sets in SWATShare tend to fall in a more physically meaningful range. In calibrated models from both tools, averaged manning's n values are similar.

There are some other limitations of this study and uncovered topics that are important to the study. First, for SWAT calibration, the best parameter set is considered as the condition of the entire basin. However, with studied watersheds larger than 1000 square kilometers, whether a given parameter value can represent the condition of watersheds in this size needs to be examined. Secondly, the inadequate definition of models would also lead to uncertainties. For example, land use data of the year 2011 was used when building SWAT models, while the study period is between the years 2001 to 2010. There might be land-use changes along the study period, especially around those suburban areas where slight land use alternation will seriously affect surface runoff. Third, it is suggested that some parameters should be manually defined, and some should be removed from the process during calibration to obtain optimal results. This step was neglected in this study to compare the performance of SWAT CUP and SWATShare and feature correlations under the same criteria. Based on the findings of this study, researchers could apply not only the physical condition of a basin, but also correlations between parameters and watershed characteristics during calibration to narrow down the essential parameters, further enhance the performance of calibration. However, change the parameter range according to the results from validation is considered as involving validation data into the calibration process. Extra observation data for validation is needed to decide whether the new calibrated model is good at forecasting or not.

The initial parameter range used for SWAT CUP calibration could lead to a good result. However, the parameter values of the calibrated model are not necessarily presenting a real physical condition. The inaccurate parameter values might lead to low objective function values in validation process. The objective function values from SWAT CUP can be improved by simply setting the range of parameter values to match the SWATShare calibrated values. Constraining the parameter to a reasonable range for a model with good performance will not decrease the objective function values/ performance of a model. As from the result, SWATShare is capable of providing a reliable calibrated model.

Between the two auto-calibration software, SWATShare accurately calibrates parameter values to a realistic range using default range in most cases. Also, in some of the ecoregions, the best parameter sets in SWATShare fall in a more physically meaningful range. This result could help the decision-making process when choosing calibration method for models in certain ecoregions. For those models calibrated by SWATShare with an unsatisfactory result, the objective function values could be improved after specifying the parameters to the best-fit range given by SWAT CUP results. Also, for those watersheds which have similar satisfactory calibrated objective values from both calibrated models, constraining the parameter to a reasonable range could generate a new calibrated model that performs as good as the original one. Using the approach to constrain parameter values to a realistic range gradually can exclude some statistically satisfactory but physically meaningless models.

Overall, this study reveals how calibrated parameters are changing over watersheds from different calibration methods. The performance of SWATShare is proving to be reliable. Although some of the parameter sets are inconsistent, most of the calibrated parameters are similar from SWAT CUP and SWATShare. Due to the equifinality of model calibration, when SWATShare and SWAT CUP yield similar objective functions, whether the parameters are in a reasonable range still need to be examined. When dealing with those weak results, the objective function values can be improved after considering realistic parameter values and incorporate SWAT CUP and SWATShare in the calibration process. Due to the equifinality nature of hydrological models, there are infinite combinations of parameter sets exist. This study exams the optimal results from 2000 sets of parameters in each calibration tool and reveal the statistics of the performance between two tools in multiple watersheds. The outcome doesn't provide a solution to finding a global optimal set, but benefit future research when deciding which calibration tool to choose under limited computing resources. SWATShare is thus proven by this study that it can provide reliable calibrations.

APPENDIX

Table A-1 Uncalibrated parameter values

Station number	CN2	GW_ DELAY	ALPHA_ BF	GWQMN	GW_ REVAP	REVAP MN	CH_N2	CH_K2	CANM X	EPCO	ESCO	SFTMP	SMTMP	SMFMX	SMFMN	TIMP	SURLA G	SOL_ AWC	SOL_K
02294898	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02374250	Varies	41.00	0.48	1746.04	0.14	365.08	0.15	12.54	0.00	0.21	0.84	2.14	5.00	0.32	6.35	0.52	14.88	Varies	Varies
02478500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02414715	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02223000	Varies	26.71	1.00	2857.15	0.04	0.01	0.07	93.97	0.00	0.97	0.98	2.06	2.22	5.71	9.37	0.86	9.55	Varies	Varies
02196000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02130980	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02387500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01189500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
03455000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
03528000	Varies	25.76	0.83	4126.99	0.07	246.04	0.08	83.41	0.00	0.75	0.34	5.00	0.22	10.00	8.25	0.06	8.03	Varies	Varies
02074000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01672500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01608500	Varies	39.41	0.12	396.83	0.15	79.37	0.01	5.00	0.00	0.94	0.43	0.40	1.11	5.56	5.40	0.98	19.44	Varies	Varies
01614500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01473500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01400500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01426500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01526500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01066000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01046500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
04067958	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
01017000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02425000	Varies	31.00	0.05	1000.00	0.02	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02318500	Varies	37.51	0.17	3333.34	0.13	158.74	0.05	100.00	0.00	0.32	0.83	3.33	-2.00	2.54	4.60	0.67	11.45	Varies	Varies
01030500	Varies	31.00	0.05	1000.00	0.02	750.00	0.01	0.00	0.00	1.00	0.95	0.50	1.00	0.50	4.50	1.00	4.00	Varies	Varies
01054000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02317500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02414500	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies
02473000	Varies	31.00	0.05	1000.00	0.20	750.00	0.01	0.00	0.00	1.00	0.95	1.00	0.50	4.50	4.50	1.00	4.00	Varies	Varies

Table A-2 SWATShare calibrated values

Station Number	CN2	GW_ DELAY	ALPHA _BF	GWQMN	GW_ REVAP	REVAPMN	CH_N2	CH_K2	CANMX	EPCO	ESCO	SFTMP	SMTMP	SMFMX	SMFMN	TIMP	SURLAG	SOL_AWC	SOL_K
02294898	Varies	35.92	0.19	1004.77	0.11	39.69	0.14	100.00	0.00	0.07	0.03	2.22	-1.44	6.98	2.70	0.84	0.05	Varies	Varies
02374250	Varies	44.65	0.14	4841.27	0.19	23.82	0.05	68.33	0.00	0.01	0.95	3.65	2.22	10.00	6.35	0.97	10.6944	Varies	Varies
02478500	Varies	40.37	0.26	1904.77	0.01	23.82	0.06	93.97	0.00	0.01	1.00	0.87	1.67	2.70	3.49	1.00	4.6119	Varies	Varies
02414715	Varies	40.68	1.00	396.83	0.06	119.06	0.04	98.49	0.00	0.62	0.89	2.78	0.00	1.27	6.83	0.19	10.3143	Varies	Varies
02223000	Varies	36.40	0.87	396.83	0.10	95.25	0.04	77.38	0.00	0.69	0.39	2.78	5.00	9.68	5.40	0.81	19.4381	Varies	Varies
02196000	Varies	33.70	0.81	634.93	0.15	214.29	0.08	18.57	0.00	0.75	0.98	0.95	0.33	7.78	6.19	0.62	20.9587	Varies	Varies
02130980	Varies	40.05	0.50	238.10	0.11	206.36	0.15	1000.00	0.00	0.95	0.94	0.56	0.44	4.44	4.92	0.84	20.9587	Varies	Varies
02387500	Varies	21.95	0.14	3095.24	0.07	238.10	0.12	100.00	0.00	0.01	0.65	3.73	-1.00	2.22	0.00	0.37	0.8103	Varies	Varies
01189500	Varies	24.49	0.03	2936.51	0.19	476.19	0.13	100.00	0.00	0.01	0.64	3.02	1.56	5.87	1.11	0.05	10.3143	Varies	Varies
03455000	Varies	38.78	0.04	158.74	0.14	134.93	0.13	100.00	0.00	1.00	0.28	3.65	-0.44	0.63	0.00	0.56	12.2151	Varies	Varies
03528000	Varies	21.79	0.06	396.83	0.17	269.85	0.13	53.25	0.00	0.83	0.73	2.54	-1.78	9.37	0.16	0.97	8.0333	Varies	Varies
02074000	Varies	21.95	0.01	79.37	0.02	373.02	0.13	26.11	0.00	0.75	0.67	3.33	0.50	4.50	4.50	0.24	11.0746	Varies	Varies
01672500	Varies	39.10	0.25	476.20	0.18	31.76	0.13	30.63	0.00	0.86	0.76	3.81	1.67	3.02	9.21	0.87	3.4714	Varies	Varies
01608500	Varies	30.05	0.48	396.83	0.08	452.38	0.08	54.76	0.00	0.25	0.83	0.24	-0.89	3.02	1.59	0.24	19.0579	Varies	Varies
01614500	Varies	22.59	0.15	952.39	0.07	198.42	0.05	47.22	0.00	0.07	0.86	0.00	0.56	4.13	0.79	0.46	19.8183	Varies	Varies
01473500	Varies	24.17	0.65	158.74	0.05	246.04	0.05	51.75	0.00	0.48	0.91	1.11	-0.44	0.32	3.02	0.08	0.4302	Varies	Varies
01400500	Varies	32.11	0.53	952.39	0.01	0.01	0.02	66.83	0.00	0.51	0.56	0.00	0.67	0.16	1.43	0.95	6.1325	Varies	Varies
01426500	Varies	37.51	0.42	1507.95	0.13	126.99	0.13	96.98	0.00	0.37	0.69	0.56	4.22	0.63	5.24	0.90	2.7111	Varies	Varies
01526500	Varies	23.22	0.69	317.47	0.05	198.42	0.08	84.92	0.00	0.89	0.83	0.08	4.11	1.11	4.13	0.00	23.6198	Varies	Varies
01066000	Varies	27.03	0.14	158.74	0.10	444.45	0.07	1000.00	0.00	0.37	0.43	2.46	-1.22	0.16	5.24	0.03	14.8762	Varies	Varies
01046500	Varies	23.54	0.05	634.93	0.12	63.50	0.15	57.78	0.00	0.31	0.37	0.40	-1.00	1.59	5.87	0.02	11.8349	Varies	Varies
04067958	Varies	41.00	0.14	317.47	0.15	39.69	0.14	48.73	0.00	0.26	0.03	0.08	3.78	5.87	3.33	0.71	21.3389	Varies	Varies
01017000	Varies	21.63	0.45	476.20	0.03	222.23	0.13	78.89	0.00	0.98	0.54	2.46	-1.22	1.59	0.79	0.35	24	Varies	Varies
02425000	Varies	21.00	0.95	158.74	0.03	7.95	0.14	98.49	0.00	1.00	0.01	4.37	2.78	2.06	8.73	0.41	22.4794	Varies	Varies
02318500	Varies	27.51	0.48	952.39	0.13	428.57	0.12	95.48	0.00	0.70	0.87	1.59	1.56	5.08	6.03	0.79	14.8762	Varies	Varies
01030500	Varies	21.00	0.31	396.83	0.07	357.15	0.07	100.00	0.00	0.73	0.92	1.19	1.56	2.54	4.60	0.24	5.3722	Varies	Varies
01054000	Varies	32.11	0.43	238.10	0.01	95.25	0.03	95.48	0.00	0.98	0.89	0.08	-0.44	0.48	5.08	1.00	1.1905	Varies	Varies
02317500	Varies	25.76	0.26	714.29	0.07	23.82	0.14	0.00	0.00	0.03	0.98	4.21	0.11	6.83	1.11	0.35	4.9921	Varies	Varies
02414500	Varies	39.10	0.87	238.10	0.04	158.74	0.06	92.46	0.00	0.48	0.04	3.10	1.00	6.51	2.54	0.94	16.777	Varies	Varies
02473000	Varies	39.73	0.32	1904.77	0.13	380.95	0.07	81.90	0.00	0.10	0.32	2.62	-0.89	6.19	9.05	0.13	0.4302	Varies	Varies

Table A-3 SWAT CUP calibrated values

Station number	CN2	GW_ DELAY	ALPHA _BF	GWQM N	GW_ REVAP	REVAPMN	CH_N2	CH_K2	CANMX	EPCO	ESCO	SFTMP	SMTMP	SMFMX	SMFM N	TIMP	SURLA G	SOL_ AWC	SOL_K
02294898	Varies	0.00	0.26	2637.54	0.12	205.68	0.20	172.16	0.00	0.58	0.34	1.32	-0.89	1.91	8.41	1.00	24.00	Varies	Varies
02374250	Varies	197.69	0.06	3010.77	0.11	231.07	0.09	45.88	0.00	0.01	0.88	0.33	1.16	1.68	2.03	0.57	8.54	Varies	Varies
02478500	Varies	175.27	0.45	1177.73	0.14	314.08	0.13	97.92	0.00	0.46	0.06	2.45	3.82	5.09	1.84	0.95	17.65	Varies	Varies
02414715	Varies	131.18	0.70	0.00	0.20	85.95	0.03	75.84	0.00	0.59	0.34	-1.77	5.02	11.03	2.71	0.28	15.51	Varies	Varies
02223000	Varies	234.03	0.90	0.00	0.09	224.41	0.07	4.33	0.00	0.65	0.22	3.28	3.24	10.28	2.11	0.12	19.92	Varies	Varies
02196000	Varies	0.00	0.14	463.34	0.15	292.30	0.09	4.24	0.00	0.31	0.52	5.17	0.84	3.50	4.15	0.55	11.08	Varies	Varies
02130980	Varies	46.79	0.52	592.16	0.06	500.00	0.10	61.07	0.00	1.00	0.64	0.34	-0.57	7.42	0.00	0.84	11.08	Varies	Varies
02387500	Varies	170.96	0.06	4199.65	0.07	334.09	0.10	86.59	0.00	0.17	0.55	5.33	-0.27	6.12	0.51	0.77	10.94	Varies	Varies
01189500	Varies	0.00	0.00	2257.76	0.09	0.00	0.12	117.53	0.00	0.64	0.51	5.78	1.19	3.12	9.28	0.51	0.05	Varies	Varies
03455000	Varies	408.87	0.31	302.33	0.08	212.77	0.15	96.26	0.00	1.00	0.15	5.22	-1.28	10.58	3.75	0.36	7.88	Varies	Varies
03528000	Varies	445.08	0.06	741.89	0.07	226.41	0.10	41.99	0.00	0.72	0.83	3.09	2.47	11.52	2.20	0.06	16.93	Varies	Varies
02074000	Varies	0.00	0.05	1712.16	0.08	0.00	0.20	60.58	0.00	0.81	0.12	4.06	2.29	0.22	5.49	0.36	18.71	Varies	Varies
01672500	Varies	223.67	0.58	582.16	0.14	273.62	0.10	100.92	0.00	1.00	0.67	-0.54	0.22	3.30	0.00	0.47	6.47	Varies	Varies
01608500	Varies	50.88	0.56	0.00	0.08	190.84	0.07	22.62	0.00	0.76	0.82	1.60	-1.77	8.39	0.00	0.47	19.29	Varies	Varies
01614500	Varies	47.00	0.48	916.73	0.08	96.23	0.03	129.96	0.00	0.07	0.75	0.17	1.99	0.00	5.76	0.15	0.05	Varies	Varies
01473500	Varies	38.55	0.18	894.61	0.07	405.05	0.04	20.82	0.00	1.00	0.20	0.32	0.52	10.40	5.02	0.02	5.58	Varies	Varies
01400500	Varies	35.18	0.56	476.06	0.12	162.46	0.03	45.75	0.00	0.68	0.65	4.71	-2.69	0.13	3.23	0.45	8.35	Varies	Varies
01426500	Varies	53.30	0.56	0.00	0.02	372.35	0.13	50.54	0.00	0.67	0.63	-0.22	2.44	1.66	4.55	0.51	23.50	Varies	Varies
01526500	Varies	0.00	0.35	0.00	0.20	114.12	0.06	49.86	0.00	0.80	1.00	0.11	2.25	1.43	5.89	0.25	14.28	Varies	Varies
01066000	Varies	6.97	0.15	188.46	0.02	178.78	0.07	143.84	0.00	0.53	0.69	2.40	-2.57	5.68	8.97	0.00	0.05	Varies	Varies
01046500	Varies	0.00	0.08	1206.11	0.03	0.00	0.18	71.30	0.00	0.09	0.20	4.09	-2.59	8.21	5.08	0.00	24.00	Varies	Varies
04067958	Varies	205.13	0.10	90.93	0.06	84.40	0.16	45.27	0.00	0.55	0.25	0.66	4.28	10.37	0.00	0.62	18.98	Varies	Varies
01017000	Varies	34.87	0.27	5000.00	0.11	21.98	0.07	114.52	0.00	0.76	0.47	2.33	2.90	2.00	5.56	0.60	22.31	Varies	Varies
02425000	Varies	2.79	0.76	1732.51	0.04	86.76	0.08	98.81	0.00	0.94	0.40	2.92	0.80	8.63	1.75	0.66	6.15	Varies	Varies
02318500	Varies	0.00	0.36	1232.51	0.10	421.75	0.14	91.40	0.00	0.62	0.80	1.64	-0.79	9.10	6.90	0.10	20.23	Varies	Varies
01030500	Varies	0.00	0.23	987.51	0.02	270.75	0.08	67.84	0.00	0.43	0.56	1.04	1.50	2.12	8.72	0.26	7.37	Varies	Varies
01054000	Varies	0.00	0.46	922.51	0.07	83.26	0.04	97.39	0.00	0.25	0.31	0.31	0.12	3.87	5.64	0.01	2.05	Varies	Varies
02317500	Varies	0.00	0.24	777.51	0.17	360.25	0.05	95.49	0.00	0.45	0.65	3.21	-0.60	7.74	8.82	0.56	23.13	Varies	Varies
02414500	Varies	0.00	0.55	3912.50	0.10	40.26	0.15	96.53	0.00	0.38	0.46	1.70	2.60	3.80	0.52	0.57	23.65	Varies	Varies
02473000	Varies	0.00	0.55	3912.50	0.10	40.26	0.15	96.53	0.00	0.38	0.46	1.70	2.60	3.80	0.52	0.57	23.65	Varies	Varies

Table A-4 Objective function values and calibrated results_SWATShare.

Station number	SWATShare_Validation				SWATShare_Calibration			
	KGE	**NSE**	**R2**	**PBIAS**	**KGE**	**NSE**	**R2**	**PBIAS**
02294898	-2.51	-7.20	0.50	-317.43	0.77	0.72	0.76	19.60
02374250	0.51	0.56	0.60	8.58	0.57	0.24	0.35	10.80
02478500	0.56	0.16	0.51	-16.10	0.47	0.21	0.30	-19.30
02414715	0.85	0.77	0.78	-7.50	0.74	0.70	0.70	-3.00
02223000	0.30	0.34	0.42	49.00	0.60	0.42	0.49	-24.80
02196000	0.57	0.48	0.51	29.30	0.44	0.46	0.48	-21.20
02130980	-0.10	-2.14	0.17	-8.97	0.67	0.33	0.47	-9.00
02387500	-0.79	-0.71	0.02	97.30	0.28	0.11	0.16	4.70
01189500	-2.56	-8.43	0.49	-284.10	-0.21	-0.31	0.30	112.10
03455000	0.22	0.19	0.22	15.60	0.20	0.15	0.16	-7.70
03528000	0.28	-0.20	0.11	-23.51	0.17	0.01	0.11	5.30
02074000	0.20	0.27	0.34	5.90	0.54	0.40	0.43	-12.60
01672500	0.63	0.23	0.42	5.26	0.74	0.52	0.57	-8.60
01608500	0.52	0.23	0.32	-17.70	0.55	0.39	0.40	-8.50
01614500	0.58	0.57	0.58	6.96	0.61	0.49	0.49	-3.40
01473500	0.53	0.07	0.64	17.70	0.77	0.67	0.72	-16.40
01400500	0.84	0.74	0.75	-3.45	0.85	0.78	0.78	-2.20
01426500	0.56	0.06	0.44	8.14	0.81	0.71	0.73	-11.80
01526500	0.70	0.58	0.70	-18.70	0.72	0.67	0.68	-12.40
01066000	0.81	0.62	0.67	-2.40	0.85	0.74	0.75	-0.90
01046500	0.40	0.17	0.25	13.50	0.53	0.40	0.42	-9.40
04067958	0.53	0.16	0.54	32.40	0.75	0.52	0.63	-12.60
01017000	0.30	0.41	0.55	44.20	0.48	0.43	0.45	-21.60
02425000	-0.01	0.11	0.43	55.42	0.04	0.13	0.51	-54.50
02318500	0.56	0.68	0.76	12.66	0.78	0.74	0.74	1.00
01030500	0.81	0.73	0.74	8.00	0.77	0.77	0.78	-4.80
01054000	0.45	-0.15	0.36	36.60	0.41	0.01	0.38	-37.20
02317500	0.36	0.33	0.33	1.82	-0.11	-2.19	0.14	18.80
02414500	0.80	0.68	0.73	-12.60	0.64	0.56	0.56	-11.80
02473000	0.55	0.41	0.42	10.60	0.66	0.35	0.45	-8.60

Table A-5 Objective function values and calibrated results_SWAT CUP.

Station number	**SWAT CUP_Validation**				**SWAT CUP_Calibration**			
	KGE	**NSE**	**R2**	**PBIAS**	**KGE**	**NSE**	**R2**	**PBIAS**
02294898	-1.85	-4.92	0.62	-244.98	0.86	0.79	0.80	-5.50
02374250	0.29	0.34	0.39	3.52	0.32	0.26	0.27	6.00
02478500	0.68	0.34	0.48	8.10	0.49	0.37	0.36	10.70
02414715	0.78	0.75	0.76	-10.70	0.70	0.70	0.71	-2.30
02223000	0.53	0.43	0.43	3.97	0.54	0.46	0.47	16.90
02196000	0.44	0.25	0.29	14.70	0.56	0.56	0.51	16.00
02130980	-1.90	-2.67	0.23	-47.30	0.61	0.40	0.34	-2.00
02387500	0.20	0.23	0.36	34.10	0.23	0.17	0.14	14.30
01189500	-1.18	-2.76	0.39	-57.60	-0.18	-0.12	0.03	-58.80
03455000	0.31	0.08	0.16	1.73	0.40	0.23	0.26	7.00
03528000	0.16	-0.03	0.09	-26.20	0.03	0.10	0.10	-6.30
02074000	-0.14	0.00	0.03	16.98	0.40	0.24	0.27	11.20
01672500	0.47	0.26	0.47	-42.60	0.74	0.63	0.64	-9.10
01608500	0.61	0.40	0.43	-7.20	0.55	0.45	0.46	15.00
01614500	0.62	0.58	0.59	8.56	0.67	0.49	0.51	1.40
01473500	0.79	0.58	0.63	-3.10	0.79	0.67	0.68	-0.20
01400500	0.76	0.68	0.69	7.80	0.81	0.73	0.73	5.20
01426500	0.53	0.03	0.45	-13.20	0.79	0.75	0.77	-14.60
01526500	0.71	0.54	0.70	-7.30	0.69	0.65	0.68	23.00
01066000	0.68	0.34	0.48	-3.18	0.86	0.71	0.73	0.60
01046500	0.53	0.29	0.35	9.87	0.59	0.39	0.45	16.90
04067958	0.60	0.19	0.52	-7.90	0.78	0.56	0.61	-2.90
01017000	0.38	0.40	0.45	31.60	0.49	0.36	0.38	14.50
02425000	0.05	0.19	0.46	61.40	0.07	0.17	0.50	62.30
02318500	0.61	0.73	0.78	16.90	0.75	0.73	0.74	14.40
01030500	0.70	0.57	0.71	16.60	0.83	0.77	0.79	13.30
01054000	0.36	-0.52	0.42	52.20	0.36	-0.21	0.50	52.60
02317500	0.20	0.28	0.36	19.90	0.79	0.60	0.63	3.20
02414500	0.49	0.49	0.55	26.70	0.66	0.54	0.55	-5.60
02473000	0.59	0.17	0.44	-16.60	0.58	0.47	0.49	17.30

Table A-6 Sensitivity analysis

Station number	Sensitivity1	Sensitivity2	Sensitivity3	Sensitivity4	Sensitivity5
02294898	TIMP	SOL_K	SMTMP	ALPHA_BF	REVAPMN
02374250	SOL_AWC	CANMX	TIMP	SMFMN	SMFMX
02478500	ALPHA_BF	SMFMN	SMFMX	SOL_AWC	TIMP
02414715	CANMX	SMTMP	REVAPMN	SOL_AWC	SFMX
02223000	CANMX	SFTMP	SURLAG	SOL_K	TIMP
02196000	SURLAG	GW_REVAP	SMTMP	CH_K2	TIMP
02130980	CANMX	SURLAG	EPCO	SMFMX	GW_REVAP
02387500	SOL_AWC	GW_DELAY	CANMX	ESCO	EPCO
01189500	SMFMX	SOL_AWC	CANMX	SMTMP	SOL_K
03455000	SOL_AWC	CANMX	GW_REVAP	SMFMX	EPCO
03528000	GWQMN	SMTMP	REVAPMN	TIMP	SURLAG
02074000	SOL_AWC	SFTMP	EPCO	CANMX	REVAPMN
01672500	TIMP	SMFMN	CANMX	SMFMX	REVAPMN
01608500	CANMX	SMTMP	SMFMN	SOL_AWC	TIMP
01614500	TIMP	CANMX	REVAPMN	GW_DELAY	GW_REVAP
01473500	GW_REVAP	CANMX	GWQMN	EPCO	SOL_AWC
01400500	SOL_K	REVAPMN	SFTMP	SMFMX	SURLAG
01426500	SOL_AWC	SURLAG	GWQMN	SMFMN	SMTMP
01526500	GW_DELAY	REVAPMN	SOL_K	SURLAG	CANMX
01066000	SMFMX	GW_REVAP	SMTMP	SURLAG	SMFMN
01046500	CANMX	REVAPMN	SOL_K	SMFMN	CN2
04067958	SURLAG	SMTMP	GW_REVAP	REVAPMN	CANMX
01017000	GW_DELAY	GWQMN	ESCO	SOL_AWC	GW_REVAP
02425000	SMFMX	SURLAG	TIMP	SFTMP	SMTMP
02318500	CANMX	SFTMP	SURLAG	SOL_K	TIMP
01030500	EPCO	SOL_K	ESCO	GW_REVAP	SOL_AWC
01054000	REVAPMN	CANMX	SOL_K	SURLAG	SOL_AWC
02317500	REVAPMN	SMFMN	SURLAG	CANMX	SOL_K
02414500	CANMX	SMFMX	SURLAG	SMFMN	GW_REVAP
02473000	SMFMN	CANMX	REVAPMN	SURLAG	SOL_K

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