Open Access Journal

Journal of Sustainable Research in Engineering 1 (2) 2014, 40-44

Journal homepage: www.jkuat-sri.com/ojs/index.php/sri/index

Comparison of two Calibration-uncertainty Methods for Soil and Water Assessment Tool in Stream Flow Modeling

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Abstract-Hydrological models are increasingly being used as decision support tools in water resource management. It is therefore important that these models undergo calibration and uncertainty analysis before their application. This study addresses the application and comparison of two calibration-uncertainty methods for a distributed model in the Upper Tana Basin. The Generalized Likelihood Uncertainty Equation (GLUE) and Sequential Uncertainty Fitting Ver. 2 (SUFI-2) were used in this study to calibrate the Soil and Water Assessment Tool (SWAT). The performance of the GLUE and SUFI-2 was evaluated using three objective functions namely: coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE) and coefficient of determination divided by coefficient of regression (bR^2). Uncertainty statistics used were the *P-factor* and *R-factor*. The study established the best method for calibration and uncertainty analysis is SUFI-2.

Keywords-Calibration, Generalized Likelihood Uncertainty Equation, Sequential Uncertainty Fitting version 2, Soil and Water Assessment Tool, Uncertainty analysis

1. Introduction

Hydrological models are widely used to simulate hydrologic responses and play an important role in management of water resources [1], [2]. Distributed and physically based hydrologic models such as the Soil and Water Assessment Tool (SWAT) must be calibrated before use because they require many parameters that cannot be directly measured [3]. This is done in order to reduce the uncertainty associated with the model prediction. The major sources of uncertainty are model structure, model parameters and input data. Model uncertainty could be due to processes occurring in the watershed but not included in the model, simplification of the processes in the model and processes unknown to the modeler and not included in the model. Parameter uncertainty is caused by parameter non-uniqueness and input uncertainty is a result of errors in input data [4]. Many calibration-uncertainty methods have been developed in the last two decades to account for these uncertainties.

These methods can be divided into three categories: a) methods that do not have rigorous statistical assumptions or ad-hoc modifications to existing statistical approaches such as Generalized Likelihood Uncertainty Equation (GLUE) [5] and Sequential Uncertainty Fitting version 2 (SUFI-2) [6]. These approaches try to represent all uncertainties by an enhanced parameter uncertainty. b) Methods that account for effect of model structural and input errors on the output by an additive error model which introduces temporal correlation of the residuals. c) Improved likelihood functions that explicitly represent input errors and/or model structural error of the underlying hydrological model [7].

Despite the large number of suggested methods, a few studies have been carried out to compare calibration-uncertainty methods. GLUE, Parameter Solution (ParaSol) and Markov Chain Monte Carlo (MCMC) [8],

[9] methods were compared in Chaohe Basin, China and it was found that despite big differences in concepts and performance, they led to similar prediction uncertainty bands [7]. Particle Swarm Optimization (PSO) [10], Differential Evolution Adaptive Metropolis (DREAM) and SUFI-2 methods were compared and it was found that the calibration and validation results indicated statistically insignificant differences among the three algorithms [4]. Five global optimization algorithms: Genetic Algorithms (GA) [12], Shuffled Complex Evolution (SCE) [13], PSO, differential evolution, and artificial immune system were compared and the results showed that genetic algorithms (GA) outperforms the other four algorithms given model evaluation numbers are larger than 2000, while PSO can obtain better parameter solutions than other algorithms given fewer number of model runs (less than 2000) [11].

In this paper, GLUE and SUFI-2 calibration-uncertainty analysis methods for SWAT were applied to 4BE01 Upper Tana sub-watershed in Kenya. Performance of the GLUE and SUFI-2 was evaluated using three objective functions, namely coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE) and coefficient of determination divided by coefficient of regression (bR^2). The uncertainty statistics used are the *P-factor* and *R-factor* which compare observation signal with the 95% prediction band [6], [14].

2. Materials and methods

2.1. Upper Tana sub-watershed

The Upper Tana sub-watershed 4BE01, which covers an area of 397 km^2, is in Murang'a County (Fig. 1). It lies between longitudes 36.58°E and 37.14°E and between latitudes 0.40°S and 0.50°S.

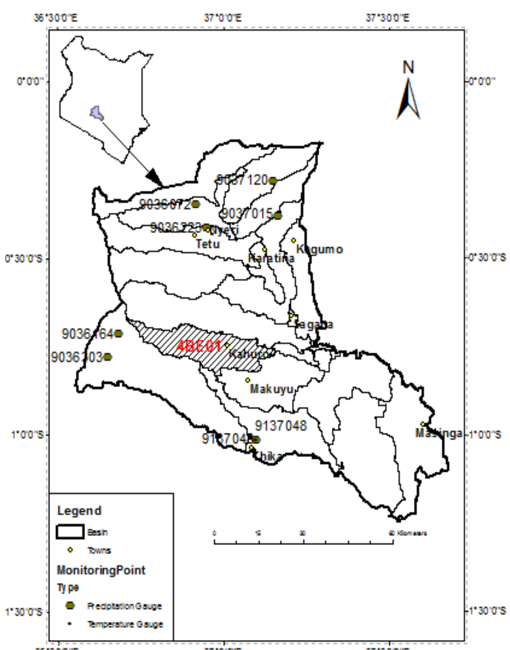

Fig. 1. Location of the study site

2.2. Generalized Likelihood Uncertainty Equation

Generalized Likelihood Uncertainty Equation (GLUE) was introduced to allow for non-uniqueness of parameter sets during the estimation of model parameters in over-parameterized models. The procedure is simple and GLUE assumes that, in the case of large over-parameterized models, there is no unique set of parameters, which optimizes goodness-of fit-criteria [15]. In GLUE, all sources of parameter uncertainties are accounted for in the parameter uncertainty [16]. The likelihood measure value, which is associated with a parameter set, reflects all sources of error and the effects of covariation of parameter values on the model performance [7]. A GLUE analysis consists of the following three steps:

1) After the definition of the generalized likelihood measure $L(\theta)$, a large number of parameter sets are randomly sampled from the prior distribution and each parameter set is assessed as either behavioral or non-behavioral through a comparison of the likelihood measure with the given threshold value.

2) Each behavioral parameter is given a likelihood weight according to:

$$w_i = \frac{L(\theta_i)}{\sum_{k=1}^{N} L(\theta_k)} \qquad (1)$$

where N is the number of behavioral parameter sets.

3) Finally, the prediction uncertainty is described as prediction quantile from the cumulative distribution realized from the weighted behavioral parameter sets. The most frequently used likelihood measure for GLUE is NSE [17].

2.3. Sequential Uncertainty Fitting version 2

Sequential Uncertainty Fitting version 2 (SUFI-2) follows a different methodology to obtain posterior parameters from priors but is conceptually similar to GLUE. Parameter uncertainty in SUFI-2 accounts for all sources of uncertainty such as uncertainty in input data, model parameters and conceptual model. It is also convenient to use [18]. The disadvantage of this method is that it is semi-automated and the modeler's interaction is needed to check the suggested posterior parameters, hence, a good knowledge on the parameters and their effect on the model output are needed [7]. The degree to which the calibrated model accounts for all uncertainty is quantified by a measure known as p-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). A SUFI-2 analysis consists of the following steps:

1) In the first step, an objective function $g(\theta)$ and physically meaningful absolute minimum ($\theta_{abs\,\min}$) and maximum ($\theta_{abs\,\max}$) ranges for the parameters are defined.

2) Sensitivity analysis for all the parameters is then carried out and then initial uncertainty ranges are assigned to the parameters for the first round of Latin hypercube sampling.
3) Latin Hypercube sampling is carried and the corresponding objective functions evaluated. The sensitivity matrix J and the parameter covariance matrix C are calculated according to

$$j_{ij} = \frac{\Delta g_i}{\Delta \theta_j}, \text{ i=1,…..,} c_2^m, j\text{=1,….,}n, \tag{2}$$

where c_2^m is the number of rows in the sensitivity matrix (equal to all possible combinations of two simulations), and j is the number of columns (number of parameters).

$$c = s_g^2 (J^T J)^{-1} \tag{3}$$

Where s_g^2 is the variance of the objective function values resulting from the n runs.
4) The 95% prediction uncertainties (95PPU) is then calculated. Then the p-factor and R-factor are calculated [15].

2.4. Soil and Water Assessment Tool

The Soil and Water Assessment Tool (SWAT) is a physically based, watershed scale model designed to predict the impact of land management practices on water, sediment and agricultural chemical yields [19]-[20]. Major input datasets include weather, topography, hydrography, land use/land cover data, soils and management practices. SWAT is computationally efficient because it is able to run simulations of very large watersheds or management practices without consuming large amounts of computational time or resources. SWAT divides a watershed into sub basins connected by a stream network and further delineates each sub basin into Hydrologic Response Units (HRUs), which consist of unique combinations of soil type, slope and land cover. HRU delineation can minimize a simulation's computational costs by lumping similar soil and land use areas into a single unit [19].

2.5. Soil and Water Assessment Tool model setup

The model setup involves the following processes: (1) watershed delineation; (2) HRU analysis; (3) definition of the weather stations; (4) editing model databases; (5) simulation. The simulation of spatially distributed hydrological processes using SWAT requires datasets for topography [21], land use/cover [22], soil types [23], climate and river discharge. A Digital Elevation Model was used for watershed delineation and topographic analysis. Land use and soil data were used in creating the HRU's by determining the parameters for each land-soil category simulated within each sub watershed. Once the HRUs were created weather data was imported into the model. This consisted of daily rainfall and temperature data. After completing the set-up, the model was run to simulate the river discharge. A summary of the datasets used is shown in Table 1 whereas, Table 2 shows the river gauge and rainfall station used respectively.

Table 1. Data used in the study

Name of data	Source of data	Period
Digital Elevation Model(DEM)	Shuttle Radar Topography Mission (SRTM)	2008
Land use/Land Cover map	Food and Agriculture Organization	2003
Soil Classification map	International Soil Reference and Information Centre (ISRIC)	2004
Daily precipitation	Kenya Meteorological Department	1970-2009
Daily Maximum/Minimum Temperature	Kenya Meteorological Department	1981-2009
Stream flow	Water Resource Management Authority (WRMA)	1945-2012

Table 2: Stream flow and rainfall station used in the study

Type	Station ID	Name	Longitude (Deg)	Latitude (Deg)	Start Year	End Year	% data missing
Stream flow	4BE01	Maragwa	-0.75	37.15	1972	1976	0.02
Rainfall	9036164	South Kinangop Forest station	-0.72	36.68	1972	1976	0.1

2.6. Criteria for the Comparison

The R^2, NSE and bR^2 objective functions were used. In order to quantify the goodness of calibration/uncertainty performance, the P-factor, which is the percentage of data bracketed by the 95% prediction uncertainty band (95PPU) (maximum value 100%) and the R-factor, which is the average width of the band divided by the standard deviation of the corresponding measured variable were used [14].

3. Results and discussion

3.1. Sensitivity analysis and calibration

Sensitivity analysis was carried out using the global sensitivity method and ten parameters were found to be more sensitive (Table 3).

Table 3. Stream flow calibration parameters

Stream flow parameter	Description
CN2.mgt	Curve Number
ALPHA_BF.gw	Base flow alpha factor
GW_DELAY.gw	Groundwater delay time
GWQMN.gw	Threshold depth of water in shallow aquifer required for return flow
GW_REVAP.gw	Groundwater 'revaporation' coefficient
REVAPMN.gw	Threshold depth of water in the shallow aquifer for 'revaporation' to occur
SOL_AWC.sol	Available water capacity of the soil layer
ESCO.hru	Soil evaporation compensation factor
SOL_K.sol	Soil hydraulic conductivity
CH_K2.rte	Effective hydraulic conductivity in main channel

Calibration was done using data between 1972 and 1976, and on monthly basis. Model calibration was done using the ten parameters that were found to be most sensitive. SUFI-2 was run six times with each iteration having 500 simulations. After every iteration, new parameter uncertainty ranges that were to be used for the next iteration were suggested. This requires that the user has a good knowledge on how the parameters affect stream flow. Comparison was done using the last run. GLUE was run four times with each run having 1000, 2500, 3500 and 5000 respectively. The comparison was made using the run with 5000 simulations. The model efficiency was measured using the three objective functions and two uncertainty statistics mentioned earlier. These objective functions were analyzed for both SUFI-2 and GLUE uncertainty analysis techniques as shown in Table 4.

Table 4: Calibration results

	SUFI-2	GLUE
R^2	0.64	0.61
NS	0.49	0.42
bR^2	0.46	0.40
p-factor	0.15	0.03
R-factor	0.04	0.05

A graphical presentation of the simulated and observed stream flow for the calibration period was plotted for visual comparison for both procedures i.e. SUFI-2 and GLUE (Fig. 2).

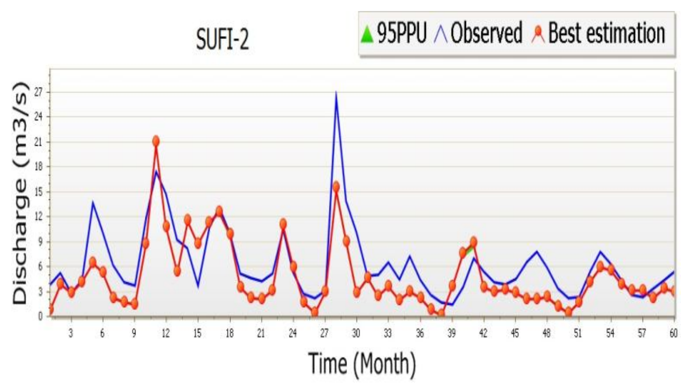

Fig. 2(a) Stream flow calibration at 4BE01 by SUFI-2

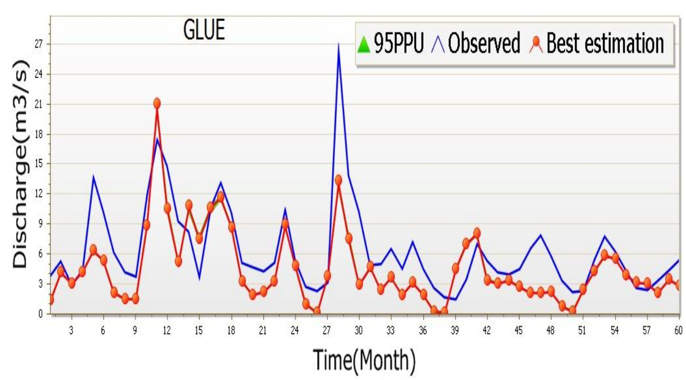

Fig. 2(b) Stream flow calibration at 4BE01 by GLUE

About 15% and 3% of the data were bracketed by the 95PPU for SUFI-2 and GLUE uncertainty methods respectively. This shows that SUFI-2 accounts for uncertainties better than GLUE. These model uncertainties can be due to errors in parameterization, model inputs and data preparation. The coefficient of determination R^2 is 0.64 and 0.61 for SUFI-2 and GLUE respectively. The results show significance in the model efficiency and SUFI-2 has a higher efficiency than GLUE. The Nash-Sutcliffe was 0.49 for SUFI-2 and 0.42 for GLUE.

4. Conclusion

SUFI-2 generally performed better than GLUE. It also accounted for uncertainties better than GLUE. It can be run with the smallest number of runs for computational demanding models. However, it requires that the user has a good knowledge on how the parameters affect stream flow. In spite of the larger number of simulations in GLUE, it cannot provide results better than SUFI-2. The disadvantage of the GLUE method is its excessive computational burden due to its random sampling strategy. This study therefore establishes that the best calibration uncertainty method is SUFI-2.

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