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CALIBRATION AND UNCERTAINTY ANALYSIS OF SWAT MODEL IN A JAPANESE RIVER CATCHMENT

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Calibration and uncertainty analysis is necessary to perform the best estimation and uncertainty identification of hydrological models. This paper uses the Soil and Water Assessment Tool-Calibration and Uncertainly Procedures (SWAT-CUP) model to analyze the uncertainty of SWAT model in a Japanese river catchment. The GLUE and SUFI-2 techniques used in this analysis show quite good results with high value of R^2 as 0.98 and 0.95 for monthly simulation. Daily simulation results during calibration and validation are also good with R^2 as 0.86 and 0.80. For uncertainty results, the 95% prediction uncertainty (95PPU) brackets very well with the observation. The p-factors of uncertainty analysis for the calibration and validation periods are 92% and 94%. The calibration result by using GLUE shows better than that by using SUFI-2. However, the processing time of the GLUE approach is longer than SUFI-2 approach when they were run in the SWAT-CUP. The uncertainty analysis indicates that the parameters of effective hydraulic conductivity in main channel alluvium (CH_K2) and base-flow alpha factor for bank storage (ALPHA_BNK) play important roles for calibration and validation of SWAT model.

Key Words: *SWAT-CUP, hydrological model, uncertainty, river catchment, SUFI-2, GLUE*

1. INTRODUCTION

With the physics-based, distributed hydrologic models widely applied for managing the flood events and water resource in the world, the calibration and uncertainty analysis of those hydrological models is complex with the limitations of the input data, the complexity of the information of hydrological processes, and uncertainty in the physical basis of a river catchment. Overestimation of uncertainty can result in over-design of mitigation measures, while underestimation of uncertainty can lead to inadequate preparation for potential situations. The fine calibration and uncertainty analysis is required for the successful application of SWAT model[1),2),3)].

The Soil and Water Assessment Tool (SWAT) [4)] is a physics-based, long-term, and distributed hydrological model. As an excellent assessment model for hydrological modeling and water resource management, the SWAT model has been applied worldwide. Many of the applications have been driven by the needs of various government agencies, particularly in the U.S.[5),6)] and the European Union, which require direct assessments of anthropogenic, climate change, and other influences on a wide range of water resources or exploratory assessments of model capabilities for potential future applications. Specially, there are several successful applications on studying the impact of climate change on water resources in India, assessing water supply and sedimentation issues in the Yellow River of China[7], and assessing water availability in the African continent[8].

There are some researches about parameter estimation[9], split-parameter structure[10], and automatic calibration[11] of hydrological models which have been done in the previous studies. The calibration of the SWAT model has been studied in multi-sites using a single-objective optimization method and the multi-objective method [12]. A multi-objective automatic calibration of SWAT model by using NSGA-II is presented by Bekele and Nicklow[13]. Calibration of SWAT model based on satellite data provided a new approach to solve the lack of reliable data[14]. A combined method by using Genetic Algorithms and Bayesian Model Averaging were used to provide a practical and flexible tool to attain reliable deterministic simulation and uncertainty analysis of SWAT[15].

The main objectives of this research are to assess the calibration and uncertainty of the SWAT model in the upper stream of the Yoshino River, and to compare two uncertainty analysis methods. In addition, we compare the performances of the estimation and computational efficiency for both Generalized Likelihood Uncertainty Estimation (GLUE) and the Sequential Uncertainty Fitting (SUFI-2).

2. STUDY SITE & DATA COLLECTION

The study site is located at the upper stream of the Yoshino River, Kochi Prefecture, Japan. The Sameura Dam (**Fig.1**) is used for hydropower, flood control, tap water, and irrigation. The Yoshino River is the second longest river in the Shikoku Island, and spreads over the four prefectures of this island. Over 80% of the Yoshino River basin area is covered by forest, 15% is the land for agriculture, and 2% is urban area. It has a long history in flood control which started from 1585 of Edo period. After 1920, the dams and artificial channels were constructed to solve the drought problem in this area. The large economical loss was caused from the drought events in recent years.

The basin area of the upper stream in the Yoshino River is about 389 km^2. The highest elevation is 1890 m, and the lowest elevation is 313 m. The forest is covered 88%, the agriculture land is only 1.5% and the urban area is 0.1% in this catchment. The annual rainfall in the mountain area

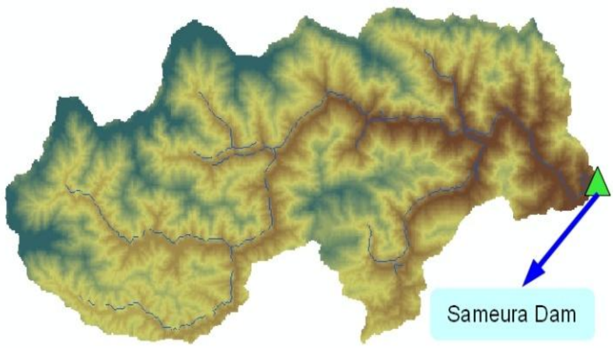

Fig.1 The boundary, river channel and digital elevation model (DEM) information of the Yoshino River upper stream

of this catchment is 2500 to 3000 mm, and the rainfall period is concentrated in rainy season and typhoon season. The extreme historical recorded discharge in the Sameura Dam is 0 m^3/s during the drought season and 4000 m^3/s during the flood season.

In this study, we collected a digital elevation model (DEM), land use, soil type, channel network, observed discharge and AMeDAS data from the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT). The 50–m resolution DEM data (**Fig.1**) and 100-m land use data are obtained from the National and Regional Planning Bureau of MLIT. The channel network and soil type are obtained from the Land and Water Bureau of MLIT. Six years' observed daily discharge data is used for the model calibration and validation.

As the input data for the weather generator of SWAT, the daily temperature, humidity, wind speed and precipitation data are used. We combined and transferred the original polygon land use data to the land use raster map by using ArcGIS9.3.

3. METHODS

(1) SWAT model

The SWAT model is continuously developed and refined by the U.S. Department of Agriculture (USDA) – Agricultural Research Service (ARS) and scientists at universities and research agencies around the world. It is a long-term, continuous simulation watershed model designed to evaluate the impacts of management conditions on water yield, sediment yield, and non-point source loadings in the watershed which is divided into a number of sub-basins called hydrologic response units (HRUs) in partition. All the input data such as land use map, soil map, DEM and so on are overlapped in order to produce HRUs, and each HRU is assumed to be spatially uniform.

There are two major divisions for the simulation of the watershed hydrology in SWAT. The land phase of hydrology cycle is the first division. The amount of water, sediment, nutrient and pesticide loadings to the main channel in each subbasin is controlled by this hydrology cycle. The routing phase of the hydrology cycle is the second division which can be defined as the movement of water, sediment and so on through the channel network of the watershed to the outlet.

The water balance equation is the base of the hydrology cycle simulation in SWAT:

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \quad (1)$$

where SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day i (mm), t is the time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), w_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm), Q_{gw} is the amount of return flow on day i (mm H2O).

(2) SWAT-CUP model

SWAT-CUP (Calibration and Uncertainty Procedures) is developed for integrating various calibration and uncertainty analysis programs of SWAT model. In this program, it includes five approaches such as Sequential Uncertainty Fitting (SUFI-2)[16),17)], Generalized Likelihood Uncertainty Estimation (GLUE)[18)], Parameter Solution [19)], Mark chain Monte Carlo[20)], and Particle Swarm Optimization for the calibration or uncertainty analysis. SUFI-2 is the algorithm for calibration of SWAT model. GLUE is a common method for the global sensitivity analysis. Generally, GLUE and SUFI-2 can provide the widest marginal parameter uncertainty intervals of model parameters among the five approaches. Therefore, the SUFI-2 and GLUE methods were applied in this study. The brief descriptions and procedures of SUFI-2 and GLUE are given as below.

a) SUFI-2

The parameter uncertainty is calculated from all the input and output source uncertainties such as the uncertainty in the input rainfall data, the user land use and soil type, parameters, and observed data, in SUFI-2. The simulation uncertainty is quantified by the 95% prediction uncertainty (95PPU) which is referred to as the p-factor. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution function of the output variable obtained by Latin hypercube sampling. The p-factor (the percent of observations bracketed by the 95PPU) and the r-factor are calculated as following Eq. (2)

$$r - factor = \frac{\frac{1}{n}\sum_{t_i=1}^{n}(y^M_{t_i,97.5\%} - y^M_{t_i,2.5\%})}{\delta_{obs}} \quad (2)$$

where $y^M_{t_i,97.5\%}$ and $y^M_{t_i,2.5\%}$ are the upper and low boundary of the 95PPU. δ_{obs} is the standard deviation of the observed data.

The best calibration and parameter uncertainty is measured by the basis of the closeness of the p-factor to 100% (i.e. all the observations bracketed by the prediction uncertainty) and the r-factor to 1 (i.e., achievement of rather small uncertainty band) [22)]. If the two factors are in satisfactory values, a uniform distribution in the parameter hypercube is explained as the following parameter distribution. The goodness fit in SUFI-2 is quantified by the R^2 and Nash-Sutcliff (NS) coefficient between the observation data and the best simulation.

b) GLUE

Generalized Likelihood Uncertainty Estimation (GLUE) which is an uncertainty analysis technique inspired by importance sampling and regional sensitivity analysis[23)]. In GLUE, parameter uncertainty accounts for all sources of uncertainties, i.e., input uncertainty, structural uncertainty, parameter uncertainty and response uncertainty, because the likelihood measure value is associated with a parameter set and reflects all these sources of error and any effects of the covariation of parameter values on model performance implicitly[24)]. The parameter uncertainty is counted by the likelihood weights of the behavioral parameter set. The likelihood weight of each behavioral parameter set is calculated as the following Eq.(3):

$$w_i = \frac{L(\theta_i)}{\sum_{k=1}^{N} L(\theta_k)} \quad (3)$$

where $L(\theta)$ is a large number of parameter sets which are randomly sampled from the prior distribution and each parameter set. N is the number of behavioral parameter sets.

In this research, R^2 and Nash-Sutcliffe objectives are applied for uncertainty measures, and the 95PPU is also used for presenting the uncertainty of the output variable. The most frequently used likelihood measure for GLUE is the Nash-Sutcliffe coefficient (NS):

$$NS = 1 - \frac{\frac{1}{n}\sum_{t_i=1}^{n}(y^M_{t_i}(\theta) - y_{t_i})^2}{\sum (y_{t_i} - \bar{y})^2} \quad (4)$$

where n is the number of the observed data points, and y_{t_i} and $y^M_{t_i}(\theta)$ represent the observation and model simulation with parameters θ at time t_i, respectively, and $\bar{y}$ is the average value of the observations.

4. RESULT AND DISCUSSION

In this research, the calibration period is from 2003 to 2005, and the validation period is from 2006 to 2008. In order to calibrate and validate the SWAT model by using the observed stream flow data, we selected 10 parameters such as Initial SCS runoff curve number (CN2), Base-flow alpha factor (ALPHA_BF), Groundwater delay time (GW_DELAY), Manning's "n" value for the main channel (CH_N2), Effective hydraulic conductivity in main channel alluvium (CH_K2), Base-flow alpha factor for bank storage (ALPHA_BNK), Available water capacity of the soil layer (SOL_AWC), Saturated hydraulic conductivity (SOL_K), Moist bulk density (SOL_BD), and Snowfall temperature (SFTMP) based on the sensitivity analysis of these parameters for the discharge calibration through SWAT-CUP model.

(1) Monthly calibration and validation

The best estimation result is obtained from the GLUE uncertainty analysis method. The time series of the simulated and observed monthly stream flow is shown in **Fig.2**. It shows a good estimation of base-flow in the calibration period (2003-2005). The simulated discharge has been overestimated in the March and April of 2004. The observed stream flow in the September of 2004 is higher than the simulated stream flow. The river discharge in 2003 and 2005 has been reproduced very well (**Fig.2**).

The simulated and observed peak discharge in 2005 shows the best result. The scatter plot of monthly stream flow for the calibration period is drawn in **Fig.3**, which shows a well fitting relationship between observation and simulation with 0.98 of likelihood measure R^2 closed to 1.

The simulated monthly discharge for validation period is also conducted in this research. For the highest peak discharge, the simulated discharge performs very well comparing with the observed discharge. For the other peak discharges, the simulated ones are slightly higher than the observed ones. It shows a fine fitting with a 0.95 R^2 likelihood measure value between the estimation discharge and observed discharge in **Fig.4**.

(2) Daily calibration and validation

The simulated daily stream flow in the calibration period presents a fine result closing to the observed data. The R^2 and NS coefficients of the best simulation result in GLUE are about 0.86 (**Fig.5**) and 0.85, respectively. An extreme peak daily discharge which is about 2800 m^3/s was found in this calibration period. The estimation result of this extreme discharge is shown in a well fitting

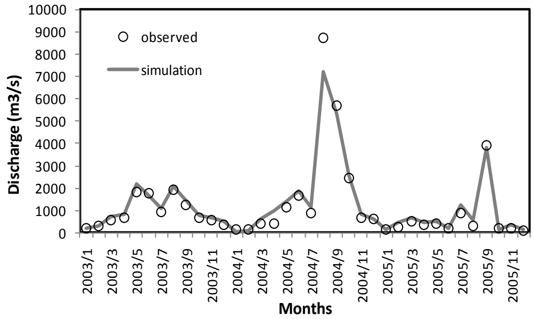

Fig.2 Time series of monthly river discharges (2003-2005)

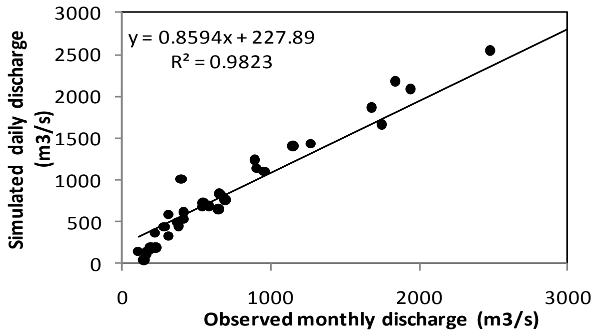

Fig.3 Scatter plot of monthly river discharges (2003-2005)

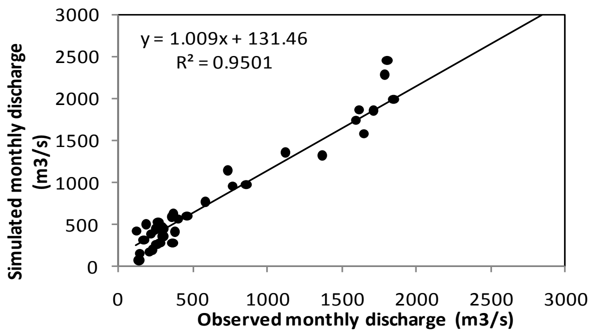

Fig.4 Scatter plot of monthly river discharges (2006-2008)

with the observed discharge. The simulated peak discharge in the most periods of the calibration performs very well.

For the validation, the estimated result also performs very well, and the coefficient of the simulated discharge was obtained as about 0.8 in the R^2 likelihood measure (**Fig.6**) and 0.73 in the NS likelihood measure.

(3) Uncertainty analysis and discussion

The threshold value of GLUE uncertainty analysis method is selected to be 0.7. For example, if the simulations with NS values larger than 0.7 are behavioral, otherwise they are non-behavioral. In the GLUE method, the sample sizes of GLUE simulation are given 1000, 5000, 10000, 20000. The sample size of this uncertainty analysis is based on 5000. The 95PPU of the model result for calibration is shown in **Fig.7**. Most of the 95PPU are bracketed by the observation and best simulation. In the base-flow part in **Fig.7**, the 95PPU is shown very clearly. The p-factor of the uncertainty analysis is 92% during the calibration period and 94% during validation period.

The uncertainty analysis of daily river discharge during validation period is shown in **Fig.8**. The 95PPU does not fit the observed river discharge well in the peak discharge of August 2006. However, the base flow has been reproduced well.

As for SUFI-2, five hundred was chosen as the sample size since similar results were obtained if the sample sizes which are greater than 500 were applied. As for GLUE, the suggested sample size in SWAT-CUP model is the value of more than 5000. In this study, five thousand was finally selected by using the trial and error method. As results, the 95PPU brackets 93% of the observations during the whole calibration period. The 95PPU is quite suitable to bracket the observations in 2003, 2005, 2007 and 2008, while are somehow overestimated or underestimated in 2004 and 2006. It means there is a lot of uncertainty in the calculation of recession parts by SWAT.

The fitted parameter values are quite different in the GLUE and SUFI-2 approaches. The fitted CN2 value in SUFI-2 is 78, but that in GLUE is 62. The best estimated value of ALPHA_BF in GLUE is about 0.89 which is four times larger than that in SUFI-2. The parameters of CH_K2 and ALPHA_BNK have much impact on the model sensitivity. The best estimated values of CH_K2 and ALPHA_BNK are 123.32 and 0.25, respectively.

For the highest peak discharge during the calibration period, the result from GLUE method is better than that from SUFI-2. The results of the likelihood measure R^2 during the calibration period are in the same value reached to 0.86 of GLUE and SUFI-2, but the results of NS likelihood measure are 0.85 of GLUE and 0.84 of SUFI-2. During the validation period, the NS likelihood measure of GLUE and SUFI-2 are 0.73 and 0.69. According to this result, GLUE performances a better result in validation than SUFI-2. The marginal parameter intervals of GLUE are wider than those of SUFI-2 because GLUE considers parameter correlations while SUFI-2 does not. SUFI-2 is limited to find one of many regions in a multidimensional parameter space. The processing time of GLUE is relatively longer than SUFI-2 in the same computing condition. This is partly because the sample size of GLUE (=5000) is much larger than that of SUFI-2 (=500).

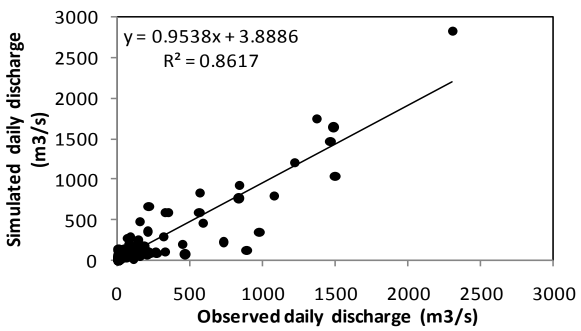

Fig.5 Scatter plot of daily river discharges (2003-2005)

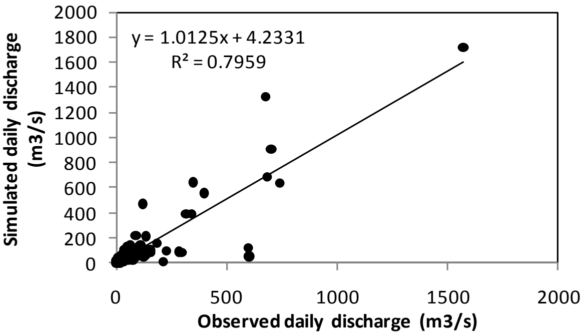

Fig.6 Scatter plot of daily river discharges (2006-2008)

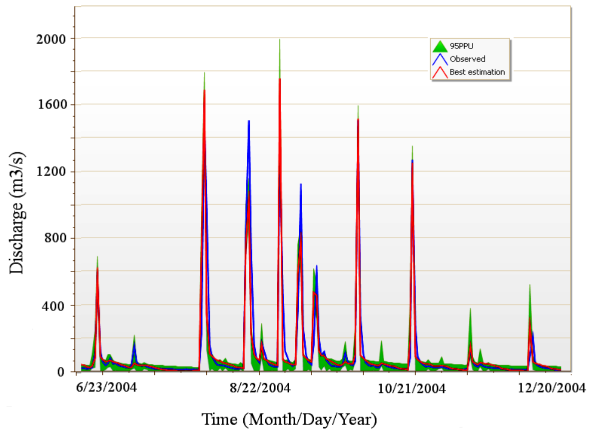

Fig.7 Uncertainty analysis of daily river discharges during calibration period (95PPU is the 95% prediction uncertainty band which is calculated at the 97.5% and 2.5% levels of the cumulative distribution function of the output variables).

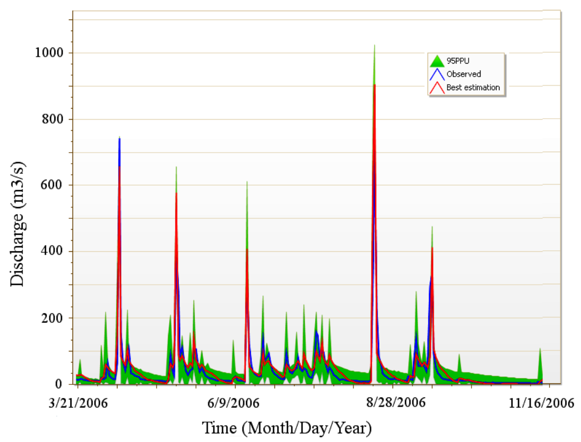

Fig.8 Uncertainty analysis of daily river discharges during validation period.

5. CONCLUSIONS

This study performed a fine result of calibration and uncertainty analysis in the upper stream of the Yoshino River. The results with the likelihood measure R^2 and NS are 0.86 and 0.85 during the calibration period, and 0.80 and 0.73 during the validation period. The 95PPU brackets with the observation in the calibration and validation periods. The comparison of GLUE and SUFI-2 applied in this Japanese river catchment suggested that the result from GLUE had the best estimation, especially during the validation period. The GLUE application led to the widest parameter uncertainty intervals of the model parameters. The SUFI-2 method can be run with the smallest sample size and in a high processing time. However, further efforts are required to conduct the sensitivity analysis of each parameter of the SWAT model in application to Japanese river catchments.

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