Applicability of SWAT Model for Streamflow Simulation in a Highly Managed Agricultural Watershed
-Case Study: Yasu River Basin, Japan-

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Abstract: Modelling is inevitable as far as strategic planning and decision making are of concern. However, natural systems such as hydrology tend to be complex when it comes to modelling. Coupled with many variables and numerous uncertainties, hydrological modelling presents an enormous task especially on distributed or semi-distributed models.

This study applies Soil Water Assessment Tool (SWAT) 2012 model for long term daily streamflow simulation in Yasu River Basin. Automatic irrigation from the reach is considered in paddy fields. Two reservoirs along the main channel are included in the model. Simulation period ranges from the year 1990 to 2009 inclusive of a two year warm up period. Sequential Uncertainty Fitting Algorithm (SUFI-2) is used as optimization program for model calibration, validation, parameter statistical significance and uncertainty analysis. Calibration is conducted from 1992 to 2000 whereas validation is from 2001 to 2009. The performance of the model is determined by coefficient of determination (R²) and Nash-Sutcliffe (NS). SWAT provided a suitable platform for hydrological modelling of Yasu River basin with relatively good performance for streamflow simulation.

Key words: Simulation; Yasu River Basin; Streamflow; Soil Water Assessment Tool

1 Introduction

Water is a natural renewable resource vital for human survival. All aspects of society and development are supported by fresh water and inland water bodies. Water cycle plays a key role in ecosystem health, and supports basic human needs and cultural uses. Water use cuts across municipal, industrial, agricultural and energy sectors. Agricultural sector outstands all other sectors when it comes to water utilization in the world. It accounts for about 70% of abstracted fresh water to cater for irrigation (Vapnek et al., 2009).

Increasing population and subsequent demand for resources to improve living standards among other external forces are increasing pressure on local and regional water supplies for irrigation, energy production, industrial and domestic purposes. Climate change on the other hand is posing a threat to water availability by depleting water sources (UNESCO, 2012; Abbaspour et al., 2015). Increased pollution by chemical and biological waste from agricultural and industrial effluent on rivers, lakes, groundwater aquifers and other fresh water sources adds to the challenges facing water availability (Sivakumar, 2011).

Addressing these challenges has been hindered by lack of comprehensive understanding of hydraulic and climatic system. They not only behave in a non-linear manner but also their interaction is complex as well (Gourbesville, 2008). It is of great importance to put effort in understanding the natural system of hydrology prior to confronting these critical issues.

One of the fundamental requirements in water resource assessment, development and management is watershed modelling. It is utilized in various ways as analyzing the quality and quantity of streamflow, reservoir system operations, groundwater development and protection, water distribution system, and water use among other management activities (Singh and Woolhiser, 2002; Wurbs, 1998).

Dynamic interactions amid climate and surface hydrology as well as the impact of climate change on water resources and agricultural productivity are achieved through watershed models. For environmental and water resource protection, impact of watershed management strategies associating human activities with quality and quantity of water within the watershed is also conducted through watershed models (Singh and Woolhiser, 2002; Mankin et al., 1999; Rudra et al., 1999).

With evolution of hydrological models over time, dynamic distributed models are increasingly being applied to address different needs in water resources management (Uniyal et al., 2015). They provide a comprehensive description of the catchment topography, computation of surface water depth, flow discharge and variation in space of infiltration and precipitation (Fernández-Pato et al., 2016). However due to complexity in natural systems, hydrological models are bound to different uncertainties which should be quantified to capture our level of ignorance. Uncertainty varies from conceptual, input and parameter uncertainties. Conceptual uncertainties are due to simplification of the conceptual model, process occurring in the watershed but not included in the model, process included in the model but their occurrence is unknown to the modeler, and process unknown to the modeler and not included in the model. Input uncertainty is attributed to error in input data and parameter uncertainty is due to inherent non-uniqueness of parameter in inverse modelling (Abbaspour, 2015). Modelling procedure requires, trans-
parent description, calibration, validation and sensitivity
and uncertainty analysis performed (Abbaspour et al., 2015).

Among different hydrological models already developed,
Soil Water Assessment Tool (SWAT) is one of the most
used. The model being process based, computationally effi-
cient, and capable of continuous simulation over long time
periods (Neitsch et al., 2011), has been applied in different
parts of the world. In Japan for instance, the model has been
used for sensitivity analyses of hydrologic and suspended
sediment discharge (Somura et al., 2009), analyzing effect
of climate change on nutrient discharge (Shimizu et al.,
2011), calibration and uncertainty analysis (Luo et al.,
2011), impact of suspended elements on nutrient loading
from land uses against water quality (Somura et al., 2012),
simulation of nutrients from an agricultural watershed
(Kato et al., 2011), modelling water balance processes for
understanding the components of river discharge (Jiang et al.,
2011), dam construction impacts on stream flow and
nutrient transport (Supit and Ohgushi, 2012), simulation of
stream nitrate-nitrogen export (Jiang et al., 2014), water
yield, nitrogen and sediment retentions (Fan and Shibata,
2016), examination of the water balance of irrigated paddy
fields (Sakaguchi et al., 2014), and estimation of phospho-
rus discharge in a suburban catchment (Shimizu et al.,
2013). Varying agro-climatic conditions in different areas
and their unique characteristics raise the need to conduct
hydrological models in different watersheds (Uniyal et al.,
2015). It is therefore important to capture the local hydro-
ological and climatic conditions.

The main objective of this study is to apply SWAT
model for long term streamflow simulation in Yasu River
basin characterized as highly managed due to human activi-
ties as agriculture dominated by irrigation and artificial
reservoirs along the main channel. Sequential Uncertainty
Fitting Algorithm (SUFI-2) is used as the optimization
techniques for model calibration, validation sensitivity and
uncertainty analysis.

2. Methodology

2.1 SWAT model

SWAT is a physically based watershed model that requires
information on weather, soil properties, topography, vegeta-
tion and land management practice in the watershed. It was
purposely developed to predict the impact of land manage-
ment practice on water sediments and agricultural chemical
yields (Neitsch et al., 2011).

The watershed is divided into subbasins where the in-
puts are categorized as: climate, hydrological response unit
(HRU), wetlands, groundwater and the main channel
drainage into the subbasin. HRU is a combination of unique
land cover, soil and slope. Hydrologic part in SWAT model
is equipped to simulate evapotranspiration, snowmelt, sur-
face runoff, infiltration, percolation, return flow, ground-
water flow, channel transmission loss, pond and reservoir
storage, channel routing, tile drainage, and plant water use
process (Arnold et al., 1999).

Land and routing phase hydraulic cycles form the basis
of watershed hydrology simulation. The amount of water,
loading to the main channel in each subbasin is controlled
by land phase hydraulic cycle while routing phase hydraulic
cycle entails loading through the channel network to the
outlet.

Surface runoff is simulated by modified Soil Conserva-
tion Service (SCS) curve number method (USGS, 1972)
and Green and Ampt infiltration method (Green and Ampt,
1911). Peak runoff rate is simulated using modified rational
method. Amount of water infiltrating the soil is calculated
as the difference between precipitation and surface runoff.
Evapotranspiration is computed from both soil and plants
based on Ritchie’s method (Richie, 1972). Potential evapo-
ration is determined by Hargreves (Hargreaves et al., 1985),
Priestely Taylor (Priestley and Taylor, 1972) and Penman
Monteith (Monteith, 1965) methods.

2.2 SUFI-2

Sequential Uncertainty Fitting Algorithm (SUFI-2) is used as
the optimization program for determining parameter sta-
tistical significance, calibration, validation and uncertainty
analysis. Its advantage over other techniques is that it re-
quires few model runs to attain good uncertainty ranges
hence more data points are captured in prediction uncertainty
(Yang et al., 2008). In comparing several optimization
techniques for uncertainty analysis, different authors
have cited advantages of SUFI-2 in terms of model perfor-
mane, prediction uncertainty and computational efficiency
over other techniques (Khoi and Thom 2015; Emam et al.,
2018). It has been termed effective in localizing optimum
parameter range in a large scale watershed simulation
(School et al., 2008; Mehan et al., 2017).

SUFI-2 depicts parameter uncertainty as ranges and ac-
counts for all sources of uncertainties expressed as 95%
probability distribution in the model output variables. This
is calculated at the 2.5% and 97.5% level of cumulative
distribution of an output variable derived using Latin hy-
cercube sampling by propagation of parameter uncertainties.
This is usually referred to as 95% prediction uncertainty
(95PPU). Sampling is carried out, leading to evaluation of
objective function corresponding to different parameter sets
in the model. The fit between simulated results, 95PPU and
observed data is quantified statistically by P-factor and
R-factor. P-factor represents the percentage of observed
data enveloped by 95PPU of the modelling results while
R-factor is the thickness of 95PPU envelope (Abbaspour,
2015). Average distance between upper and lower 95PPU is
calculated as follows:

\[
\overline{J}_X = \frac{1}{N} \sum_{i=1}^{N} (X_U - X_L) \tag{1}
\]

where \(\overline{J}_X\) is the average distance between the upper and
lower 95PPU, \(N\) is the number of observation data points,
\(X_U\) and \(X_L\) is the upper 97.5 and lower 2.5 percentiles of
cumulative distribution of every simulated point respect-
ively. \(P\)- and \(R\)-factors are computed as follows:

\[
P = \frac{\text{95PPU}}{N} \tag{2}
\]
where $\sigma_X$ is the standard deviation of the measured variable and $n^{95\text{PPU}}$ is the number of measured values bracketed by 95PPU. With significance, which is measured by $t$ test, number of hydrological parameters, sensitivity analysis is carried out to identify the most suitable parameters to be adjusted during calibration period in SUFI-2.

Multi regression analysis is used to determine the significance of parameters. It calculates partial regression coefficients which regress the generated parameters against the objective function. A $t$ test is used to identify significance of each parameter under the null hypotheses that partial regression is equal to zero. In the $t$ test, an index $t$-stat, which is defined as a partial regression coefficient divided by the standard error of the parameter, is used to estimate $p$-value from the $t$ distribution with $n-1$ degrees of freedom, where $n$ is the number of parameter sets generated. The larger the absolute value of $t$-stat the more significant the parameter is, which implies that $p$-value becomes smaller (Abbaspour, 2015).

$$R = \frac{\bar{Y}}{\sigma_X} \tag{3}$$

$$NS = 1 - \left[ \sum_{i=1}^{N} \left( \frac{Q_{\text{obs},i} - Q_{\text{sim},i}}{\bar{Q}_{\text{obs}}} \right)^2 \right] \tag{4}$$

$$R^2 = \frac{\left[ \sum_{i=1}^{N} \left( Q_{\text{obs},i} - \bar{Q}_{\text{obs}} \right) \left( Q_{\text{sim},i} - \bar{Q}_{\text{sim}} \right) \right]^2}{\sum_{i=1}^{N} \left( Q_{\text{obs},i} - \bar{Q}_{\text{obs}} \right)^2 \sum_{i=1}^{N} \left( Q_{\text{sim},i} - \bar{Q}_{\text{sim}} \right)^2} \tag{5}$$

where $Q_{\text{obs}}$ is the observed streamflow, $Q_{\text{sim}}$ is the simulated streamflow, $\bar{Q}_{\text{obs}}$ is the mean of observed streamflow and $\bar{Q}_{\text{sim}}$ is the mean of simulated streamflow.

### 2.3 Study area

Yasu River basin is located in Honshu Island Japan and lies between coordinates N 34°51’ to 35°07’ and E 135°58’ to 136°26’. It originates from Mount Gozaisho and drains into Lake Biwa. The basin has a catchment area of 387 km² with a total length of 65 km from the source to mouth. The watershed has undulating topography ranging from 97 m to 1,234 m above sea level. Four climatic seasons of summer, autumn, winter, and spring are experienced around the year. The basin receives high amount of rainfall with a mean of about 1,587 mm per annum. The location of the study area is shown in Figure 1.
2.4 Dataset

Spatial datasets includes Digital Elevation Model (DEM), land use and soil data obtained from Shiga prefecture. Figure 2 shows spatial elevation in Yasu River basin. DEM has a spatial resolution of 30 m by 30 m. It is used for watershed and subbasin delineation covering the entire process of flow direction, flow accumulation, and stream network generation. Figure 3 shows the spatial distribution of land use in the basin. The dominant land cover in the basin is forest occupying 61% of the area. Paddy fields occupy 18% of the land. Settlements, upland field, golf course, water and other land occupy 21% of the area.

Figure 4 shows the spatial distribution of soil in the basin. Soil distribution is dominated by Brown Forest soil covering (BFS) an extent of 39% of the land because a large area is under forest cover. 21% of soil data is unclassified (UNC). Immature soil (IMS) occupies 18% of the land with Gley lowland soil (GLS) covering 13%. Gley soil (GS), Yellow soil (YES), Red soil (RDS) and Andasol (AND) combined covers 9% of the land. Soil dataset serves as an input in SWAT model for formation of HRUs in the basin.

Temporal datasets comprise of climatic and hydrological data from the year 1990 to 2009. Location of hydraulic structures and weather stations are shown in Figure 5. Climate data includes precipitation, temperature, humidity, wind, and solar radiation. Four stations serve as the source of climatic data: Higashiomi, Otsu, Shigaraki, and Tsuchiyama. Hydrological data includes daily streamflow from Yasu gauging station, overflow data from Ozuchi and Yasu River Dams. Hydraulic structures regulate the amount of water in the reach. The reservoirs determine the amount of water released from the gate downstream hence the consideration of overflow as input data. Q-GIS (Quantum Geographic Information System) is used as an interface to run SWAT 2012 model. The basin is divided into 13 subbasins and 630 HRUs to represent the diversity within the basin. The length of the reach is distinctive within each subbasin. Water flow is cumulative from one reach to another as it flows from the source to the downstream end.

2.5 Irrigation management

Cultivation of rice is the major agricultural activity in the basin. Rice is characterized by high crop water requirement and the field is usually covered with water during irrigation period forming pools. In this study, however, automatic irrigation is used in the model. It triggers water application from the reach to the paddy field when the plant stress level is reaches the set criterion. Water is applied up to field capacity and the cycle continues until crop reaches its maturity. Plant water demand is used as the water stress identifier. Water stress threshold that triggers irrigation has a scale of 0 to 1. Water stress threshold of 0.2 is set to trigger irrigation to prevent plant from water deficiency. The amount of maximum water applied each time of irrigation is set as 40 mm with an irrigation efficiency of 0.5. The fraction of surface runoff ratio is set at 0.2. Irrigation source
is located at the reach of each subbasin due to headworks abstraction in the field condition. To prevent flow in the reach from being reduced to zero, minimum in-stream flow of 0.01 m³/s is set. This therefore implies that irrigation water can be diverted from the reach if the flow in the reach is above minimum in-stream flow. Maximum daily irrigation diversion from the reach is set at 100 mm. The amount of water applied to the HRU cannot exceed the maximum daily irrigation abstraction.

3. Results and Discussion

3.1 Sensitivity analysis

Significant parameters used for model calibration are shown in Table 1. They include: Soil conservation service runoff curve number (CN2.mgt), average slope length (SLSUBBSN.hru), base flow recession alpha factor (ALPHA_BF.gw), deep aquifer percolation fraction (RCHRG_DP.gw), channel effective hydraulic conductivity (CH_K2.rte), soil evaporation compensation factor (ESCO.hru), soil saturated hydraulic conductivity (SOL_K.sol), and Manning’s value of overland flow (OV_N.hru). These values of \( t \)-stat and \( p \)-value in Table 1 are average of those calculated from the eleven objective functions shown in subsection 2.2.

Table 1: Significant parameters in the study area

| Parameter       | \( t \)-stat | \( p \)-value |
|-----------------|-------------|--------------|
| v__CH_K2.rte    | 30.5        | 0.00100      |
| v__SLSUBBSN.hru | 23.9        | 6.89E-30     |
| v__OV_N.hru     | 18.2        | 0.00666      |
| v__ALPHA_BF.gw  | 24.6        | 2.15E-07     |
| v__CH_N2.rte    | 15.4        | 0.00100      |
| r__CN2.mgt      | 12.5        | 0.00108      |
| v__ESCO.hru     | 3.89        | 0.0335       |
| r__SOL_K.sol    | 2.85        | 0.0310       |

3.2 Calibration, validation and uncertainty analysis

Calibration period ranges from the year 1992 to 2000. Validation is from the year 2001 to 2009. The number of parameter sets in one iteration is 1000. Uncertainty analysis is conducted together with calibration. CN2.mgt is calibrated for different land use. Soil parameter represented by SOL_K is calibrated for different soil type and layer. Unclassified soil is assigned gleicy properties for soil database in SWAT model before calibration. Two layers are considered, (1) represents the first layer and (2) is the second layer. Fitted values for saturated soil hydraulic conductivity, and other sensitive parameters are shown in Tables 3, and 4, respectively. Parameters are adjusted by replacing the computed value with the existing value in the model denoted by \( v \) preceding the parameter, and multiplying (1+ the computed value) by the existing value denoted by \( r \). Min and Max denotes the minimum and maximum value of the range.

Table 2: Soil conservation service runoff curve number for different land use parameter

| Parameter       | Min   | Max   | Fitted |
|-----------------|-------|-------|--------|
| r__CN2.mgt_Rice | -0.56 | 0.20  | 0.184  |
| r__CN2.mgt_Upland fields | -0.57 | 0.18  | 0.092  |
| r__CN2.mgt_Settlement | -0.51 | 0.36  | 0.0285 |
| r__CN2.mgt_Forest | -0.52 | 0.34  | 0.186  |
| r__CN2.mgt_Golf course | -0.55 | 0.24  | 0.161  |
| r__CN2.mgt_Water | -0.60 | 0.06  | -0.299 |
| r__CN2.mgt_Other land | -0.56 | 0.20  | -0.0892 |

Fitted values for soil conservation service runoff curve number are shown in Table 2. Land use in the basin is classified based on SWAT land use classes therefore other land is represented by general agricultural land.

Table 3: Soil saturated hydraulic conductivity

| Parameter       | Min   | Max   | Fitted  |
|-----------------|-------|-------|---------|
| r__SOL_K(1).sol_AND | -0.5 | 0.9   | 0.339   |
| r__SOL_K(1).sol_BFS | -0.5 | 0.9   | 0.0187  |
| r__SOL_K(1).sol_GLS | -0.5 | 0.9   | -0.0093 |
| r__SOL_K(1).sol_GS | -0.5 | 0.9   | -0.336  |
| r__SOL_K(1).sol.IMS | -0.5 | 0.9   | 0.325   |
| r__SOL_K(1).sol.RDS | -0.5 | 0.9   | 0.661   |
| r__SOL_K(1).sol_UNC | -0.5 | 0.9   | 0.811   |
| r__SOL_K(1).sol.YES | -0.5 | 0.9   | 0.604   |
| r__SOL_K(2).sol_AND | -0.5 | 0.9   | 0.580   |
| r__SOL_K(2).sol_BFS | -0.5 | 0.9   | 0.160   |
| r__SOL_K(2).sol_GLS | -0.5 | 0.9   | 0.537   |
| r__SOL_K(2).sol.GS | -0.5 | 0.9   | 0.702   |
| r__SOL_K(2).sol.IMS | -0.5 | 0.9   | 0.626   |
| r__SOL_K(2).sol.RDS | -0.5 | 0.9   | 0.832   |
| r__SOL_K(2).sol.YES | -0.5 | 0.9   | 0.411   |

Table 4: Other parameters

| Parameter       | Min   | Max   | Fitted   |
|-----------------|-------|-------|----------|
| v__SLSUBBSN.hru | 10    | 150   | 0.403    |
| v__ALPHA_BF.gw  | 0     | 2     | 0.0882   |
| v__ESCO.hru     | 0     | 1     | 0.0305   |
| v__CH_K2.rte    | 0     | 150   | 0.103    |
| v__SLSUBBSN.hru | 0.001 | 0.3   | 0.0134   |
| v__CH_K2.rte    | 0.01  | 3     | 0.891    |

The results of the model performance based on \( NS \) and \( R^2 \) as well as uncertainty analysis evaluated by \( P \)- and \( R \)-factors are shown in Table 5. Hydrographs during calibration and validation periods are shown in Figures 6 and 7. Results based on evaluation performance had values greater than 0.5 for both \( NS \) and \( R^2 \), and these values are above required
threshold set for evaluation performance described in section 2.2. Observed data enclosed in 95PPU is 82% with uncertainty range of 0.48 during calibration period. Percentage of data enclosure in the 95PPU during validation period is 81% with an increase in uncertainty range compared to the calibration period. SWAT model application studies conducted within Japan have found almost similar results in model performance for daily streamflow simulation. Studies conducted in Kashima river watershed in Chiba prefecture had an average of 0.66 for $R^2$ and 0.55 for NS based on different analyses conducted. The average of $P$- and $R$-factor was 0.93 and 0.79 respectively (Sofiyuddin et al., 2016). Similar ranges have also been obtained in watershed outside Japan. Application of SUFI-2 in Agricultural watershed in South Dakota (Mehan et al., 2017) had an average of 0.57 $R^2$ and 0.56 NS for the simulation period.

Table 5: Performance evaluation and uncertainty analysis

|                | Calibration | Validation |
|----------------|-------------|------------|
| $NS$           | 0.72        | 0.56       |
| $R^2$          | 0.70        | 0.56       |
| $P$-factor     | 0.82        | 0.81       |
| $R$-factor     | 0.48        | 0.53       |

Figure 6: Observed and simulated hydrograph during calibration period

Figure 7: Observed and simulated hydrograph during validation period
and $R$-factors based on 2000 simulation was 0.94 and 0.65 respectively.

It is worth noting that total uncertainty in SUFI-2 is expressed as parameter uncertainty which leads to an equally weighted impact on wet and dry seasons. Challenges in utilizing SUFI-2 includes lacks rigorous probabilistic formulation, parameter uncertainty formulated by uniform distribution in hypercube is propagated but does not consider parameter correlation and inclusion of simulations with poor objective function values (Yang et al., 2008). Based on the results formulated from $P$- and $R$-factors, the parameter prediction uncertainty is relatively large with most of the observed data included in the 95PPU. Yasu river basin being highly managed with intensive human activity, it is bound to have numerous conceptual uncertainties. Water management also increases uncertainty within the basin. It is therefore important to capture most of the observed data under the 95PPU with minimum uncertainty range possible.

There is a notable variation in simulated peak discharge where the model under-predicts peak flow in extreme flooding events. Observed and simulated discharge however corresponds to precipitation pattern in the basin. Figures 8 and 9 show cumulative discharge and error based on ob-

![Figure 8: Cumulative discharge and error during calibration period](image)

![Figure 9: Cumulative discharge and error during validation period](image)
erved and simulated discharge during calibration and validation periods, respectively. The cumulative discharge is high in observed data as compared to simulated data for both calibration validation periods. This depicts overall underestimation of streamflow with notable errors during extreme flooding events. Figures 10 and 11 show the scattered plot of observed and simulated discharge during calibration and validation periods. It also portrays the limitation of simulated data to capture high peak values of observed data in both calibration and validation period. Several studies carried out in different catchments have reported under-prediction of peak (Ghoraba, 2015; Wu and Chen, 1999). Possible reasons for inaccuracy of peak discharge in Yasu River basin include limited meteorological stations and the extent of distance from one station to another, uncertainty in GIS information for spatial distribution of slope, land use and soil. There might also be possibilities of limitation of the observed data to accurately record peaks discharge during extreme flooding period. SWAT model underestimates peak discharge due to the simple curve number method used to model rainfall runoff relationship. Its major limitation is that rainfall intensity/duration is not accounted for. Runoff generated by short duration high intensity storm may not be simulated in a large extent (King et al., 1999).

4. Conclusion

The study provided an approach for streamflow simulation based on SWAT model in Yasu River basin. Consequently, sensitivity analysis based on parameter statistical significance, calibration, validation and uncertainty analysis were carried out using SUFI-2 as the optimization program. Auto irrigation based on crop water requirement was considered during rice cultivation. Daily overflow data from two large reservoirs along the main channel were included in the model. Long term daily streamflow was simulated. Significant parameters were used for model calibration. The model performance had values greater than 0.5 for both NS and $R^2$ during both calibration and validation period. Proportion of observed data enveloped by 95PPU was 82 and 81% with uncertainty range of 0.48 and 0.53 during calibration and validation periods, respectively. The percentage enveloped by 95PPU is relatively high considering the range of uncertainty. Yasu River basin being highly managed presents unique challenges coupled with high uncertainties when it comes to long term daily simulation.

Although the model requires significant amount of data and detailed analysis, it is vital for hydrological assessment. The model can be utilized for critical decision making on efficient utilization and management of water in Yasu River basin.

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References

[1] Abbaspour, K. C. (2015): SWAT CUP: SWAT Calibration and Uncertainty Programs- A User Manual, Eawag Swiss Federal Institute of Aquatic Science and Technology, 100p.
[2] Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., and Klöve, B. (2015): A Continental-scale Hydrology and Water Quality Model for Europe: Calibration and Uncertainty of a High-resolution Large-scale SWAT Model, Journal of Hydrology, 524, pp.733–752.
[3] Arnold, J. G., Srinivasan, R., Muttila, R. S., and Allen, P. M. (1999): Continental Scale Simulation of the Hydrologic Balance, Journal of the American Water Resources Association, 35(5), pp.1037–1051.
[4] Emam, A. R., Martin, K., Steven, F., Nguyen, H., and Khanh, L. (2018): Uncertainty Analysis of Hydrological Modeling in a Tropical Area Using Different Algorithms, Frontiers of Earth Science, https://doi.org/10.1007/s11707-018-0695-y.
[5] Fan, M., and Shibata, H. (2016): Water Yield, Nitrogen and Sediment Retentions in Northern Japan (Teshio river watershed): Land UseChange Scenario Analysis, Mitigation and Adaptation Strategies for Global Change, 21(1), pp.119–133.
[6] Fernández-Pato, J., Caviedes-Voulliémea, D., and Garcia-Navarro, P. (2016): Rainfall/Runoff Simulation with 2D Full Shallow Water Equations: Sensitivity Analysis and Calibration of Infiltration Parameters, Journal of Hydrology, 536, pp.496–513.
[7] Ghoraba, S. M. (2015): Hydrological Modeling of the Simly
Dam Watershed (Pakistan) Using GIS and SWAT Model, *Alexandria Engineering Journal*, 54(3), pp.583–594.

[8] Gourbesville, P. (2008): Challenges for Integrated Water Resources Management, *Physics and Chemistry of the Earth, Parts A/B/C*, 33(5), pp.284–289.

[9] Green, W. H., and Ampt, G. A. (1911): Studies of Soil Physics. The Flow of Air and Water Through Soils, *Journal of Agricultural Research*, 4(1), pp.1–24.

[10] Hargreaves, G. L., Hargreaves, G. H., and Riley, J. P. (1985): Agricultural Benefits for Senegal River Basin, *Journal of Irrigation and Drainage Engineering*, 111(2), pp.113–124.

[11] Jiang, R., Li, Y., Wang, Q., Kuramochi, K., Hayakawa, A., Woli, K. P., and Hatano, R. (2011): Modeling the Water Balance Processes for Understanding the Components of River Discharge in a Non-conservative Watershed, *Transactions of the ASABE*, 54(6), pp.2171–2180.

[12] Jiang, R., Wang, C. Y., Hatano, R., Hayakawa, A., Woli, K. P., and Kuramochi, K. (2014): Simulation of Stream Nitrate-Nitrogen Export Using the Soil and Water Assessment Tool Model in a Dairy Farming Watershed with an External Water Source, *Journal of Soil and Water Conservation*, 69(1), pp.75–85.

[13] Kato, T., Somura, H., Kuroda, H., and Nakasone, H. (2011): Simulation of Nutrients from an Agricultural Watershed in Japan Using the SWAT Model, *International Agricultural Engineering Journal*, 20(3), pp.40–49.

[14] Khoi, D. N., and Thom, V. T. (2015): Parameter Uncertainty Analysis for Simulating Streamflow in a River Catchment of Vietnam, *Global Ecology and Conservation*, 4, pp.538–548.

[15] King, K. W., Arnold, J. G., and Bingner, R. L. (1999): Comparison of Green-Ampt and Curve Number Methods on Goodwin Creek Watershed Using SWAT, *American Society of Agricultural Engineers* 42(4), pp.919–925.

[16] Luo, P., Takara, K., He, B., Cao, W., Yamashiki, Y., and Nover, D. (2011): Calibration and Uncertainty Analysis of SWAT Model in a Japanese River Catchment, *Journal of Japan Society of Civil Engineers, Ser. B1 (Hydraulic Engineering)*, 67(4), pp.61–66, (in Japanese with English abstract).

[17] Mankin, K. R., Koeliliker, J. K., and Kalita, P. K. (1999): Watershed and Lake Water Quality Assessment: An Integrated Modeling Approach, *Journal of the American Water Resources Association*, 35(5), pp.1069–1080.

[18] Mehan, S., Ram, P. N., and Sandeep, K. (2017): Coupling of SUFI 2 and SWAT for Improving the Simulation of Streamflow in an Agricultural Watershed of South Dakota, *Hydrology: Current Research, 8* (3).

[19] Monteith, J. L. (1965): Evaporation and the Environment, *Soc. Exp. Bio, 19*, pp.205–234.

[20] Neitsch, S., Arnold, J., Kiniry, J., and Williams, J. (2011): Soil & Water Assessment Tool Theoretical Documentation Version 2009, *Texas Water Resources Institute*, pp.1–618.

[21] Priestley, C. H. B., and Taylor, R. J. (1972): On the Assessment of Surface Heat Flux and Evaporation Using Large Scale Parameters, *Mon. Weath. Rev.*, 100, pp.81–92.

[22] Ritchie J.T. (1972): A Model for Predicting Evaporation from a Row Crop with Incomplete Cover, *Water Resour*, 8, pp.1204–1213.

[23] Rudra, R. P., Dickinson, W. T., Abedini, M. J., and Wall, G. J. (1999): A Multi-tier Approach for Agricultural Watershed Management, *Journal of the American Water Resources Association*, 35(5), pp.1159–1170.

[24] Sakaguchi, A., Eguchi, S., and Kasuya, M. (2014): Examination of the Water Balance of Irrigated Paddy Fields in SWAT 2009 Using the Curve Number Procedure and the Pothole Module, *Soil Science and Plant Nutrition*, 60(4), pp.551–564.

[25] Schuol, J., Abbaspour, K. C., Raghavan, S., and Hong Y. (2008): Estimation of Freshwater Availability in the West African Sub-Continent Using the SWAT Hydrologic Model, *Journal of Hydrology*, 352 (1–2), pp.30–49.

[26] Shimizu, Y., Odera, S., and Saito, M. (2013): Applicability of SWAT Model for Estimation of Phosphorous Discharge in a Suburban Catchment, *Journal Of Japan Society of Hydrology and Water Resources*, 26(3), pp.153–173, (in Japanese with English abstract).

[27] Shimizu, Y., Onodera, S., and Saito, M. (2011): Effect of Climate Change on Nutrient Discharge in a Coastal Area, Western Japan, *IAHS-AISH Publication*, 348, pp.172–177.

[28] Singh, V. P., and Woolhiser, D. A. (2002): Mathematical Modeling of Watershed Hydrology, *Journal of Hydrologic Engineering*, 7(4), pp.270–292.

[29] Srivakumar, B. (2011): Global Climate Change and its Impacts on Water Resources Planning and Management: Assessment and Challenges, *Stochastic Environmental Research and Risk Assessment*, 25(4), pp.583–600.

[30] Sofiyuddin, H. A., Tasuku, K., and Ryota, T. (2016): Uncertainties of SWAT Model in Irrigated Paddy Field Watershed, *Journal Irisugi*, 11 (1), pp.11–22.

[31] Somura, H., Takeda, I., Arnold, J. G., Mori, Y., Jeong, J., Kannan, N., and Hoffman, D. (2012): Impact of Suspended Sediment and Nutrient Loading from Land Uses against Water Quality in the Hi River Basin, Japan, *Journal of Hydrology*, 450, pp.25–35.

[32] Somura, H., Takeda, I., and Mori, Y. (2009): Sensitivity Analyses of Hydrologic and Suspended Sediment Discharge in the Abashiri River Basin, Hokkaido Region, Japan, *International Agricultural Engineering Journal*, 18(1–2), pp.27–39.

[33] Supit, C., and Ohgushi, K. (2012): Dam Construction Impacts on Stream Flow and Nutrient Transport in Kase River Basin, *International Journal of Civil & Environmental Engineering*, 12(3), pp.1–5.

[34] UNESCO (2012): *World Water Development Report Volume 4: Managing Water under Uncertainty and Risk. UN Water Report* (Vol. 1), 380p.

[35] Uniyal, B., Jha, M. K., and Verma, A. K. (2015): Parameter Identification and Uncertainty Analyses for Simulating Streamflow in a River Basin of Eastern India, *Hydrological processes*, 29(17), pp.3744–3766.

[36] USGS (1972): *USDA Soil Conservation Service. National Engineering Handbook Section 4 Hydrology.*

[37] Vapnek, J., Aylward, B., Popp, C., and Bartram, J. (2009): Law for Water Management: A Guide to Concepts and Effective Approaches, *FAO Legislative Study* (101), 341p.

[38] Wu, H., and Chen, B. (2015): Evaluating Uncertainty Estimates in Distributed Hydrological Modeling for the Wenjing River Watershed in China by GLUE, SUFI-2, and ParaSol Methods, *Ecological Engineering*, 76, pp.110–121.

[39] Wurbs, R. A. (1998): Dissemination of Generalized Water ParaSol Methods, *IAHS-AISH Publication*, 348, pp.172–177.

[40] Yang, J., Reichert, P., Abbaspour, K. C., Xia, J., and Yang, H. (2008): Comparing Uncertainty Analysis Techniques for a SWAT Application to the Chaohu Basin in China, *Journal of Hydrology*, 358(1–2), pp.1–23.

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