ANALYZING LONG-TERM CHANGES IN WATER DISCHARGE AND SOIL CONDITION OF OGOUCHI RESERVOIR CATCHMENT

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ABSTRACT

Through effective and sustainable management, forests can contribute in soil and water resources conservation by reducing the intensity of floods and soil erosion. To clarify this relationship, modeling of long-term water discharge and quantitatively analyzing its influence to changes in watershed condition is necessary. In this study, SWAT model was used to simulate long-term water discharge of Ogouchi Reservoir catchment in Japan. Model calibration was performed by varying sensitive streamflow parameters: *Cn2* (SCS Curve Number) and *Sol_Awc* (soil available water capacity). Subsequently, model performance was evaluated every 10 years in an attempt to develop decadal trends which will describe the response of forest soils to the 56-year flow variations in the watershed. Using statistical indices and recursive digital filter method for model validation, it was found that SWAT accurately reproduced both the monthly streamflow components, surface runoff and baseflow, at wet periods where there is moderate to high flow. The high accuracy proved the applicability of SWAT in long-term discharge analysis of a steep and forested watershed like Ogouchi. Moreover, the trend of optimal *Sol_Awc* factors revealed that there may be significant change in soil condition from decade B (1969-1978) to decade F (2009-2015) which exhibits the positive effect of forest management policies implemented from the past years.

Keywords: forest maintenance, SWAT model, Ogouchi Reservoir, hydrograph separation, decadal validation

1. INTRODUCTION

Sustainable and effective forest management is considered a key factor to soil and water resources conservation. Generally, well-managed forests have direct impacts on the high quality of water yields from watersheds and on lowering flow peaks during extreme rainfall events. They also contribute to soil erosion control, and consequently, reducing the levels of sediment deposition in the downstream. (Achouri, 2002).

The previous studies confirming the relationship of forest cover changes in river discharge (Bosch and Hewlett, 1982; Bruijnzeel, 2004; Wei *et al.*, 2008) arrived at a general conclusion that logging for timber production increases the discharge, whereas afforestation and reforestation causes its reduction. However, the amount of reduction varies from one study to another which is an implication of the complex interactions among land cover, soil, climate, and other watershed properties (Zhou *et al.*, 2010).

The Tokyo Metropolitan Water Conservation Forest is the largest among the forests managed by water supply corporations in Japan. The Tokyo Metropolitan Government Bureau of Waterworks has maintained about 50% of its total area and nurtured it as a water conservation forest for over a century now. From 1910 up to present, they continuously expands the protected forest, with some changes in management practices between the decades. After 1971, logging for timber production was restricted, and starting from 1986, they implemented non-clear cutting and multi-layer planting to prevent deforestation. It has been reported that in its 60 years of operation, the Ogouchi Dam has maintained a low rate of deposited sediment at about 3.2%. However, the impacts of forest conservation in the upstream to the flow variations and forest soil condition are still being clarified.

In this study, a distributed hydro-ecological model called Soil and Water Assessment Tool (SWAT) was applied to simulate flow variations in the dominantly forested and mountainous Ogouchi Reservoir catchment. With the Government obtaining over 50 years of discharge data as part of their dam operation, it is highly plausible to validate the model predictions, and furthermore, explain the long-term relationship between river discharge and the changes in forest and soil conditions in the catchment.

2. DESCRIPTION OF THE STUDY AREA

Completed in 1957, Ogouchi Reservoir in Okutama, Tokyo is the largest exclusive water supply reservoir in Japan with a storage capacity of 185 million m^3. The study area is its 262.9-km^2 catchment located between latitudes 35°43’16” to 35°52’03” N and longitudes 138°46’59” to 139°04’32” E, as shown in Figure 1. Since the terrain is mountainous, it presents steep slopes with an elevation range from 525 to 2,103 m. The watershed is dominantly forested with some portions with grasslands, mixed shrublands, and waterbody. The average annual temperature is about 15.42°C, the highest occurring in August and lowest in January. Based on the rainfall and discharge records in the last 60 years, the average annual basin precipitation is 1,480 mm and the average daily dam inflow is 8.78 m^3/s.

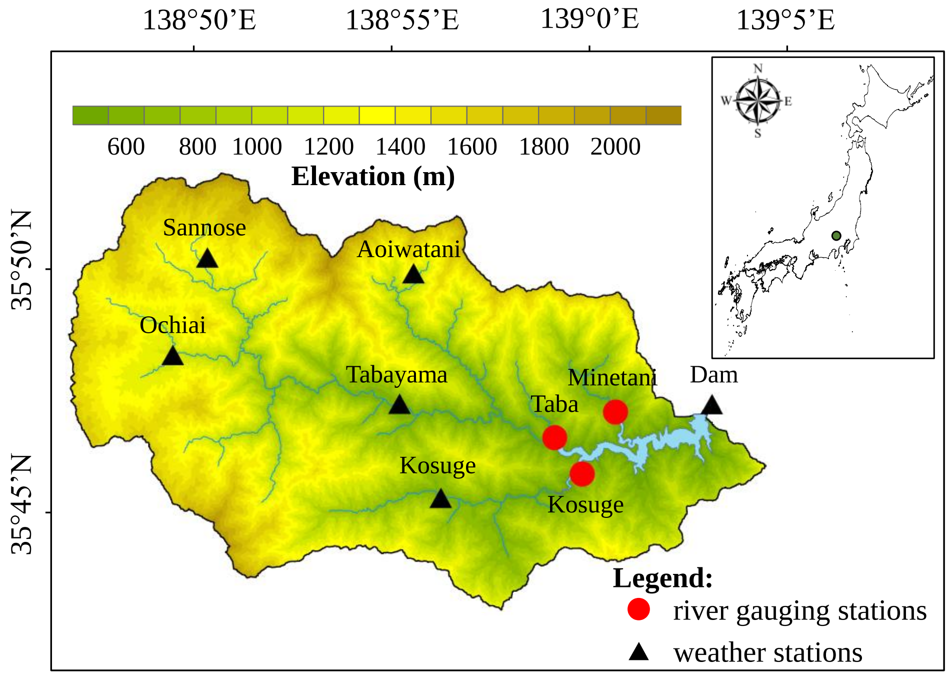

Figure 1. 10-m digital elevation model and location of the study area in Japan.

3. METHODOLOGY

3.1 Description of SWAT Model

SWAT is physically-based, conceptual, river basin-scale, continuous event model developed by the United States Department of Agriculture Agricultural Research Service (*Arnold et al.*, 1998). The watershed is divided into multiple sub-basins based on the stream network and topography; subsequently, these sub-basins are divided into several hydrologic response units (HRUs) consisting of homogenous land use, topographic, and soil characteristics (Narsimlu *et al.*, 2013). The hydrological component of the model calculates a soil-water balance at each time step based on daily amounts of precipitation R, runoff Q, evapotranspiration ET, percolation P, and return flow QR, as presented in Eq. (1).

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_i - Q_i - ET_i - P_i - QR_i) \tag{1}$$

where SW_t is the final soil water content, SW_0 is the initial soil water content, t is time in days.

Surface runoff prediction based on rainfall excess is governed by SCS curve number equation, as shown in Eq. (2) (William and Berndt, 1977).

$$Q = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \qquad S = 25.4\left(\frac{1000}{CN} - 10\right) \tag{2}$$

where Q is surface runoff (mm), R_{day} is daily rainfall (mm), S is retention parameter (mm), CN is curve number.

3.2 Preparation of Model Inputs

The required geographical inputs include the digital elevation model (DEM) of the study area, as well as its land cover and soil classification maps. On the other hand, daily rainfall and air temperature records are the minimum weather data for the program to simulate the hydrological processes in the watershed.

DEM is the primary spatial input in SWAT model and is used to determine terrain attributes such as elevation, slope, and aspect for any point in the area of interest. The DEM of the study area (Figure 1) was obtained by processing the 10-m mesh altitude data of Tokyo and Yamanashi from Geospatial Information Authority of Japan (GSI), which were previously developed from basic survey and topographic map contours.

The 2013 vegetation map from the Ministry of the Environment (MOE) was utilized to represent the land cover classification in the study area. During the initial processing, there were 51 identified specific classes of land cover but these were reclassified into more general classes based on the SWAT land use database. Upon reclassification, it was found out that the watershed consists of 65.33% deciduous forests, 22.95% evergreen forests, and 3.02% mixed forests. The remaining 8.70% is covered by grasslands, mixed shrublands, and waterbody, and a very small portion allotted for bare ground and urban area. On the other hand, the soil classification map inputted in the model was obtained from the National Agriculture and Food Research Organization (NARO). The catchment is covered with 79% brown forest soils, and the remaining 21% with andosols, immature, and clayey soils for waterbodies. The information about the physical properties of the soil are important in simulating and understanding the hydrological characteristics of the watershed such as runoff rate, peak discharge, and time of concentration. The land cover and soil classification maps used for model simulation are shown in Figure 2.

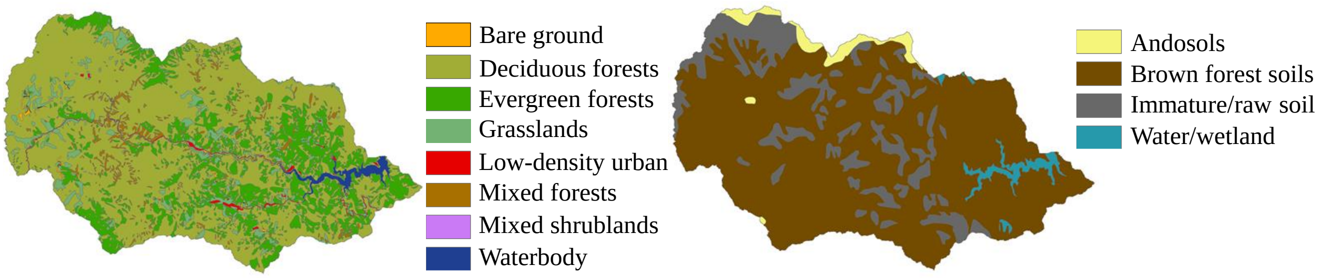

Figure 2. Land cover map (left) and soil classification map (right) of the study area.

Aside from geographical data, SWAT also requires inputs of climatic data. The time series of rainfall and air temperature from Tokyo Metropolitan Government Bureau of Waterworks and Japan Meteorological Agency (JMA) were converted into pairs of .txt files containing important information about the weather stations and the starting period of measurement.

3.3 Model Setup, Calibration, and Validation

DEM was imported in the *Automatic Watershed Delineation* feature and streams and outlets were created based on the terrain attributes along the area. The land cover and soil classification maps were overlaid to the DEM and the watershed was divided into several sub-basins. In this study, multiple HRUs with 10% land use, 20% soil, and 10% slope thresholds was used to eliminate minor land uses, soil, and slope classes in each subbasin, as recommended in the SWAT user manual (Neitsch *et al.*, 2002). Upon entering the time series of weather data, the hydrological processes at a monthly time-step were simulated from January 1, 1959 to December 31, 2015.

Two sensitive streamflow parameters, *Cn2* (SCS Curve Number) and *Sol_Awc* (soil available water capacity), were calibrated at the dam site gaging station. The model was calibrated by simultaneously adjusting these parameters until the calculations were considered acceptable, as per the model performance evaluation indices in Section 3.4. The calibrated parameters of the model were then validated every 10 years (Table 1) to describe the possible decadal changes in physical condition of the forest soils in the watershed.

Table 1. Division of study period for decadal validation.

Decade	Inclusive Years
A	1960*-1968
B	1969-1978
C	1979-1988
D	1989-1998
E	1999-2008
F	2009-2015

*1959 being warm-up period so validation for Decade A starts at 1960.

3.4 Model Performance Evaluation

In order to evaluate the accuracy of model predictions, the simulated values must be compared with the observed streamflow data. The difference between these two can be quantified by a number of statistical indices such as Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Percent Bias (PBIAS).

NSE is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance. It quantifies the variance of observed versus simulated data relative to a 1:1 best-fit line. NSE values were calculated using Eq. (3).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{3}$$

where O_i and P_i are observed and predicted values, respectively, for event i, $\bar{O}$ is the mean value of observed discharge, and n is the number of observations.

The error indices, RMSE and MAE, are valuable because they indicate error in terms of units or squared units of the constituent of interest, and hence, are easy to interpret. RMSE and MAE values less than half the standard deviation of the measured data may be considered low and desirable. RMSE and MAE were calculated using Eq. (4) and (5), respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i| \tag{5}$$

Lastly, PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. It can help identify average model simulation bias, whether it is underpredicted or overpredicted. PBIAS values were computed using Eq. (6).

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i} \times 100 \tag{6}$$

The general performance ratings for recommended statistics for monthly time step in the SWAT model (Arnold *et al.*, 1998; Moriasi *et al.*, 2007) is shown in Table 2.

Table 2. Model performance ratings for recommended statistics for monthly discharge evaluation.

Performance Rating	RSR*	NSE	PBIAS
Very good	0.00 ≤ RSR ≤ 0.50	0.75 < NSE ≤ 1.00	PBIAS < ±10
Good	0.50 < RSR ≤ 0.60	0.65 < NSE ≤ 0.75	±10 ≤ PBIAS < ±15
Satisfactory	0.60 < RSR ≤ 0.70	0.50 < NSE ≤ 0.65	±15 ≤ PBIAS < ±25
Unsatisfactory	RSR > 0.70	NSE ≤ 0.50	PBIAS ≥ ±25

*RSR is calculated as the ratio of RMSE and standard deviation of measured data.

3.5 Hydrograph Separation using Recursive Digital Filter Method

Model performance can also be evaluated using subjective inspection through hydrograph separation. The recursive digital filter (RDF) method used in signal and frequency analysis is a generally accepted scheme of hydrograph separation since high frequency waves can be treated as surface flows, and low frequency waves as base and subsurface flows. Filtering the discharge components will support the analysis of long-term and seasonal trends in direct runoff and baseflows, and particularly, in determining which combination of model parameters will produce the closest results to the actual scenario.

In this study, the RDF algorithm proposed by Eckhardt (2004) was used. This method utilizes two parameter filters: recession constant, α and maximum baseflow index, BFI_{max}. Eq. (7) presents the baseflow equation as a function of total flow and these two filters.

$$q_{b(i)} = \frac{(1 - BFI_{max})\alpha q_{b(i-1)} + (1 - \alpha)BFI_{max} \times q_{(i)}}{1 - \alpha BFI_{max}} \tag{7}$$

where $q_{b(i)}$ is calculated baseflow and subsurface flow at day i, $q_{b(i-1)}$ is calculated baseflow and subsurface flow at day i-1, $q_{(i)}$ is total flow at day i, α is recession constant, and BFI_{max} is maximum baseflow index.

In the case of Ogouchi Reservoir catchment which is characterized by perennial streams with porous aquifers, the value of α is 0.925 and BFI_{max} is 0.80 (Eckhardt, 2004).

4. RESULTS

4.1 Model Simulation of Long-Term Discharge

SWAT model calculated discharge for 56 years but the first year (1959) was set as warm-up period. Comparing this set of initial simulation to the observed streamflow data, the model performance ratings are as follows: NSE = 0.65, RMSE = 39.43 (RSR = 0.59), PBIAS = +34.59, and MAE = 30.39. In reference to Table 2, this prediction utilizing the default properties of input data was considered "Satisfactory". Meanwhile, the monthly hydrograph in Figure 3 shows that the model performed well in predicting peak flows during rainy seasons (May to October), but underestimated the low flows during dry periods (November to April).

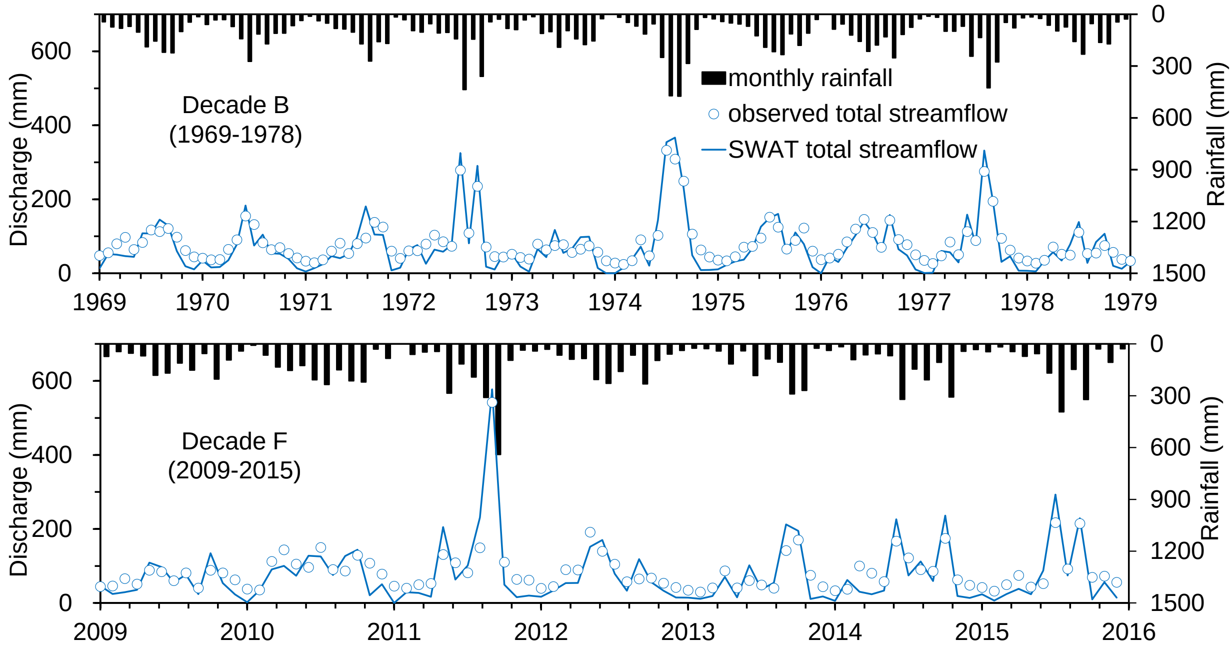

Figure 3. Monthly streamflow hydrograph at initial calculation of water discharge.

4.2 Model Validation after Initial Calibration

Figure 4 shows the resulting monthly streamflow and baseflow hydrographs after initial model calibration. NSE is highest for all decades at *Cn2* factor of 0.50. The simulation of high and moderate flows were improved, ascertained by their little deviations from the observed data. However, the calculation of low flows during dry months are still quite underestimated. In addition, the separation of hydrographs revealed that total streamflows are completely dominated by base and subsurface flows, and that surface runoff predictions were almost approaching zero, even at extreme rainfall occurring during the months of June to September.

4.3 Model Validation using Recursive Digital Filter Method

Upon readjustments of streamflow parameters, it was observed that surface runoff was well-reproduced at *Cn2* factor of 1.00 (default), which may imply that only *Sol_Awc* is changing at each decade. In addition, reliable model predictions were still achieved at default *Cn2*, in reference to the computed statistical indicators for each decade. The generated hydrographs at default *Cn2* are shown in Figure 5.

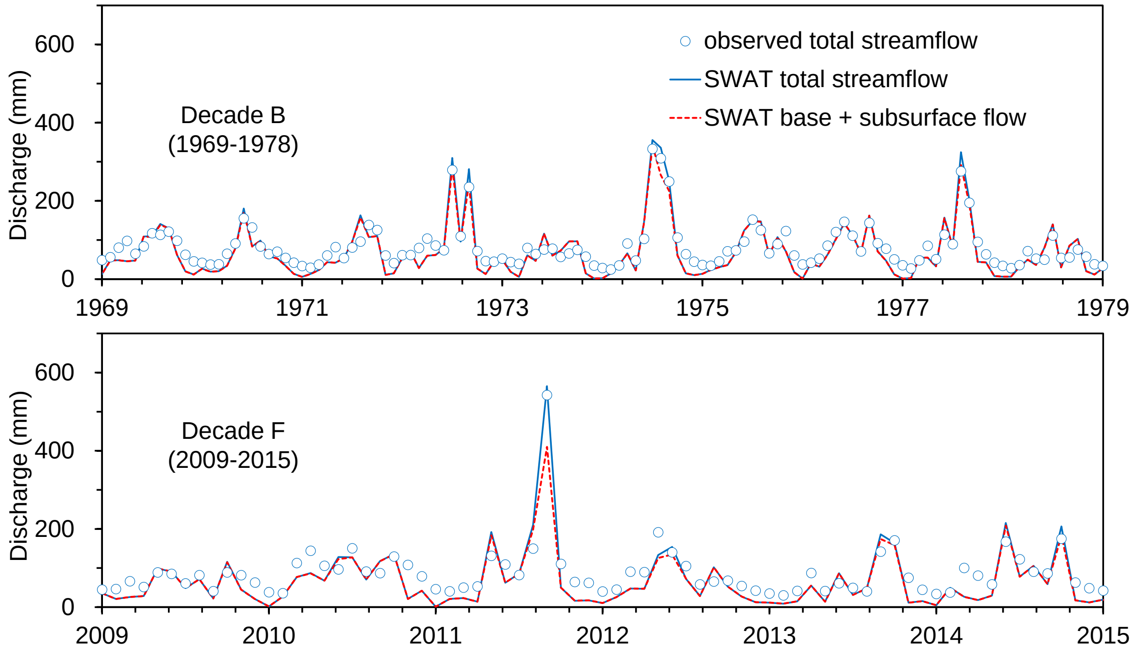

Figure 4. Monthly streamflow and baseflow hydrographs after initial model calibration.

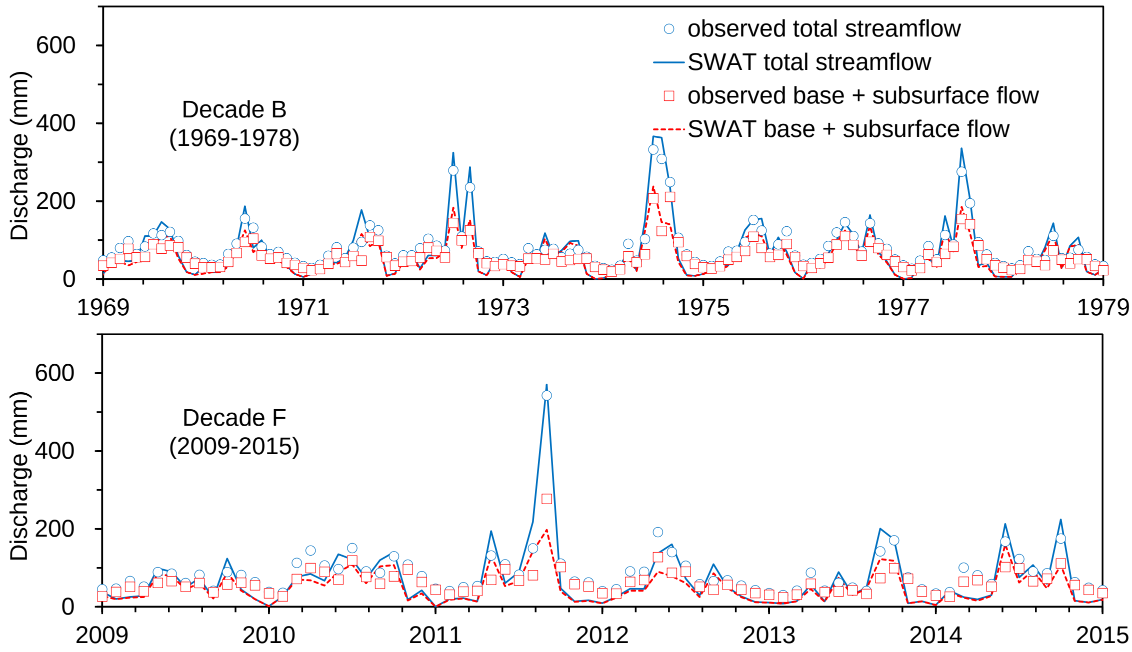

Figure 5. Monthly streamflow and baseflow hydrographs after validation using RDF.

5. DISCUSSION

As mentioned in Section 4.1, the model simulation of long-term monthly discharge was rated "Satisfactory" when subjected to 56-year validation. However, the model performance evaluation per decade in Table 3 expresses a wider view of assessing the effectiveness of the model. Predictions of water discharge for decades B, C, E, and F were classified as "Good", decade D was considered "Satisfactory", and only decade A was rated "Unsatisfactory". The possible inaccuracy and instability of discharge measurements from 50 years ago may be the reason behind the poor performance in decade A relative to the other periods.

Based on the monthly hydrograph presented in Figure 3, SWAT reliably reproduced the peak discharge in both decades and even the moderate flows in decade B. The most accurate discharge predictions can be observed from 1975 to 1977. However, in almost all years, SWAT underestimated the low flows from November to March, with the lowest predictions occurring in December and January. In the attempt to improve the performance of the model especially in these dry periods, the calibration of two sensitive streamflow parameters, *Cn2* and *Sol_Awc*, were performed. These two parameters were given the highest importance because of their relevance in describing the long-term changes in forest and soil condition based on their response to the streamflow variations.

Table 3. Model performance rating at each decade at initial calculation.

Decade	NSE	RMSE	MAE	PBIAS	Performance Rating
A	0.33	43.3	32.7	40.0	Unsatisfactory
B	0.70	30.6	26.7	32.4	Good
C	0.72	41.0	29.3	33.2	Good
D	0.60	44.3	34.7	35.8	Satisfactory
E	0.72	38.1	30.0	33.5	Good
F	0.66	38.1	33.4	38.6	Good

SCS Curve Number (*Cn2*) is an empirical parameter used for event-based estimation of surface runoff from rainfall amount. Its value is influenced by hydrologic soil group, land use and management, and antecedent soil moisture conditions. Lower values are assumed for well-managed soils because they are characterized by high permeability and low runoff potential (United States Department of Agriculture, 1986). Soil available water capacity (*Sol_Awc*), on the other hand, is the capacity of the soil to retain a significant amount of water in its intermediate layer, which are significant for plant processes and flood control. Through time, the retained water may percolate on deeper layers of the soil or drain towards the streams.

Upon repetitive adjustments of these parameters, the initial optimal value of *Cn2* factor was found to be 0.50 in all decades. Comparison between the simulated streamflows at this *Cn2* factor and observed data yielded the highest NSE. However, the very low and impractical values of SCS Curve Number resulted to unrealistic surface runoff predictions. With this, aside from statistical indicators, RDF method of hydrograph separation was also carried out to evaluate the model through visual inspection of streamflow components. Comparing the hydrographs resulted from all *Cn2*-*Sol_Awc* combinations, the *Cn2* factor that obtained the closest predictions to the observed baseflow data for the whole study period is 1.00 (default). The hydrographs presented in Figure 5 also attested a slight improvement in the prediction of low flows at dry periods.

On the other hand, the optimal *Sol_Awc* factor is yet to be determined since the trend varies per performance indicator, an implication of the major differences in error quantification among these indices. Since NSE and RMSE have almost same manner in quantifying simulation errors, similar with MAE and PBIAS (Moriasi *et al.*, 2015), only the trends of *Sol_Awc* factors based on the decadal NSE and MAE were given importance. NSE quantifies the strength of deviation from the average of observed data. Its value ranges from -∞ to 1.00, closer to 1.00 being the desired value because it implies lower difference between the simulation and the measurement. MAE, on the other hand, provide the average of the absolute difference between the observed and simulated values. NSE can be a desirable indicator for understanding peak discharge at short periods while MAE for low discharge at long periods.

Considering that decade A provided unreliable calculations, the trend of the optimal *Sol_Awc* factors from decade B to decade F based on the highest NSE and lowest MAE is shown in Figure 6. It is deemed necessary to refine the trend of the *Sol_Awc* factors at decades C, D, and E, but it can already be inferred that there is a major change in soil condition of Ogouchi Reservoir catchment from decade B (1969-1978) to decade F (2009-2015).

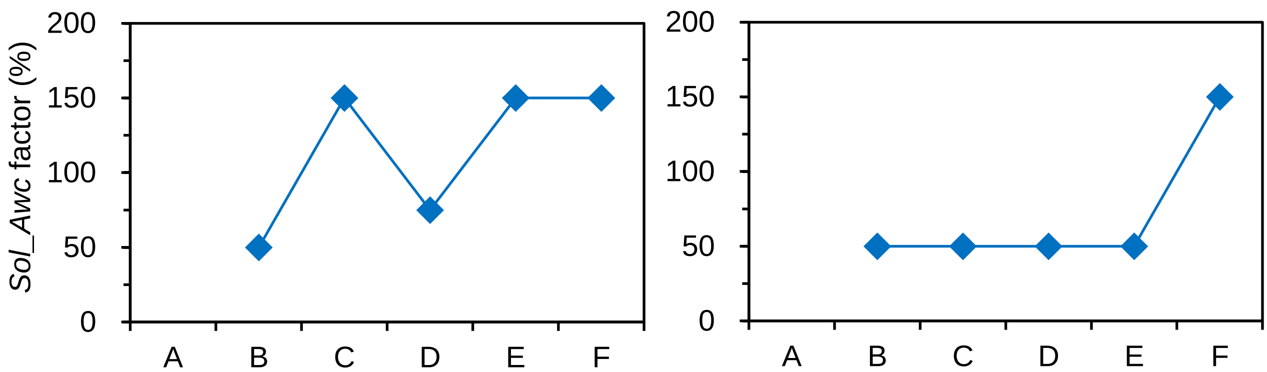

Figure 6. Trend of *Sol_Awc* factors from decade B to decade F based on NSE (left) and MAE (right).

6. CONCLUSIONS

This study analyzed the applicability of SWAT hydrologic model in long-term simulation of water discharge to clarify the changes in soil condition of Ogouchi Reservoir catchment in the past six decades. The significant findings in the analysis are as follows:

(1) Applicability of SWAT in monthly discharge modeling of a forested and mountainous catchment

The computed statistical indices were considered desirable for all periods except decade A, where the accuracy of the measured values was unstable. This implies that monthly streamflow can be accurately reproduced using the SWAT model. Since the model calculation of streamflow directly depend on the amount of rainfall, it was possible to obtain near-perfect simulations during wet periods.

(2) Validation of model accuracy using statistical indicators and visual inspection of hydrographs

Objective (statistical indicators) and subjective (hydrograph separation using filter) approaches were used to evaluate the model predictions from different *Cn2-Sol_Awc* combinations. This was to verify if both surface and subsurface flows were accurately reproduced by the model.

(3) Long-term changes in forest and soil condition

The long-term trend of *Sol_Awc* factors based on monthly predictions of water discharge showed that soil available water capacity had a dramatic increase from decade B (1969-1978) to decade F (2009-2015). Further analysis by using daily discharge predictions may be carried out to refine and validate this established trend.

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