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Evaluation of SWAT model performance on simulating hydrological processes in an agricultural watershed

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Key words: Sensitivity analysis, Calibration, Validation, SWAT model, Watershed

Abstract

The applicability of the Soil and Water Assessment Tool (SWAT) model has been demonstrated in many countries around the world with different goals and objectives. The intent of this study was to evaluate the performance of the SWAT model on simulating hydrological process in an agricultural watershed. The model is embedded within ArcGIS and integrated various spatial environmental data including information about soil features, land cover, weather and topographic features. The performance of the model was evaluated using the Coefficient of Determination (R^2) and Nash-Sutcliffe efficiency (NSE). The daily observed streamflow data obtained from the Bureau of Research and Standards under the Department of Public Works and Highways (DPWH-BRS) were utilized for the model calibration and validation and the results were found to be acceptable and reliable. Considering the good results of the SWAT model in this study, the model is very promising for land and water management studies and expected to give valuable information to authorities, policy makers, and land and water resources managers.

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Introduction

Hydrological models are becoming popular and essential in developing watershed management plans to attain better soil and water conservation measures in the region. These hydrological models are common tools used to simulate important natural processes that occur in the environment such as rainfall, runoff, evaporation, groundwater transport, vegetation growth, sediment and nutrient transport, and among others. These hydrological models also give better understanding on water resource assessment to quantify and calculate hydrological parameters from all parts of the watersheds that are essential for effective management of land and water resources especially for water-scarce region.

Among the widely used watershed hydrological models, the Soil and Water Assessment Tool (SWAT) (Arnold *et al.*, 1998) is the most accepted tool for assessing water quantity and quality, sediment transport, and streamflow in watershed. It had been successfully used in assessing impacts of climate change on watershed hydrology (Alibuyog, 2009). Its applicability has been demonstrated in many countries around the world with different modeling objectives, including streamflow simulation and prediction (Beiger *et al.*, 2012; Singh *et al.*, 2013; Chattopadhyay and Jha, 2014), analysis of climate change impacts on hydrology (Alibuyog, 2010; Makundan *et al.*, 2013; Perazzoli *et al.*, 2013; Khoi and Suetsugi, 2014; Piniewski *et al.*, 2014), and pollutant loads assessment (Bosch *et al.*, 2011; Almendinger *et al.*, 2012), among other applications. Therefore, this study used SWAT hydrological model and explored its suitability and accuracy based on model effectiveness during calibration and validation period at a watershed level.

Material and methods

Description of the Study Area

The hydrologic modeling performed in this study focuses on the Abuan Watershed. The studied watershed located at the western edge of the Sierra Madre with geographic coordinates of 17°11'12"N and 122°7'12"E. Based on the delineated boundary, the Abuan Watershed has a catchment area of 64,201.32 hectares that supports the livelihood of farming households of the eastern barangay of Ilagan City, Isabela.

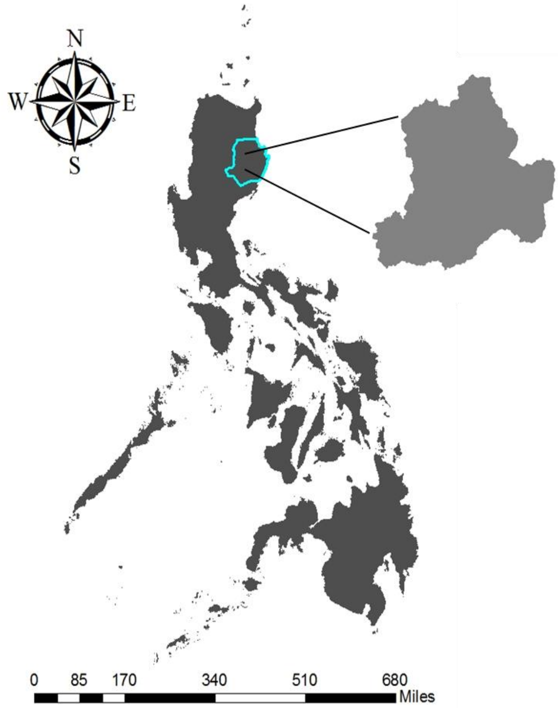

Fig. 1. The Study Area (Abuan Watershed).

Soils in the study area were classified into three major soil types, the Mountain soil, the Rugao clay soil and, the Sandy loam soil. The majority of the soils in the watershed area are Mountain soil type (96.42%) which has a medium type of runoff potential. The other two soil types, the Rugao clay soil and Sandy loam soil, have smaller areas with 0.097% and 3.48% of the watershed area, respectively. The watershed area is also covered with forest (77.62%) while 8.8% of the watershed area is planted with rice, corn and other agricultural crops. The other landuse/land cover of the area includes the grassland area (4.42%), production forest (8.84%), river (0.01%) and settlement area (0.25%). The basin falls under Type IV climate of the Coronas Climate Classification System of the Philippine Atmospheric, Geophysical and Astronomical Sciences Administration (PAGASA). The watershed generally received an average annual rainfall of 2532.18mm and average annual maximum and minimum temperature of 31.3°C and 22.09°C respectively.

The SWAT Model

The Soil and Water Assessment Tool is a continuous, long term, physically distributed model designed to predict the impact of land management practices on the hydrology, sediment yield, and water quality in agricultural watersheds (Arnold *et al.*, 1998). The objectives in the model development were to predict the runoff, climate change, sediment yield, and landuse change in the catchment (Arnold and Fohrer 2005; Gassman *et al.*, 2007). The model can be used to analyse small or larger catchments by representing them into different sub-basins, which are subdivided into Hydrological Response Units (HRUs) with homogenous landuse, slope and soil types. The model is embedded within Arc GIS and integrated various spatial environmental data including information about soil features, land cover, weather, and topographic features. To simulate water balance components and sediment yield, SWAT model required data like soil data, weather data, and landuse map (Haverkamp *et al.*, 2005; Neitsch *et al.*, 2005). The SWAT model is developed and refined by the U.S. Department of Agricultural Research Service (ARS) and scientists at universities and research agencies around the world. The water balance equation (Eq. 1) is the base of the hydrologic cycle simulation in SWAT:

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

Where, SW_t is the final soil water content (mm), SW_o is 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), and Q_{gw} is the amount of return flow on day i (mm).

SWAT Model Inputs

To create a SWAT dataset, the interface need to access ArcGIS compatible raster and vector datasets (shape files and feature classes) and database files which provide certain types of information about the watershed. The necessary inputs or datasets for the ArcSWAT interface include the climate data, digital thematic maps and streamflow data.

The climatic inputs were used in the model to assess the hydrological water balances of the watershed consist of precipitation, temperature, relative humidity, wind speed, and solar radiation. Time series of meteorological data (1991-2018) was obtained from the weather station within the study area. Basic map inputs also required for the SWAT model. The basic maps includes the digital elevation model (DEM), soil map, landuse, and land cover.

Basic map inputs also required for the SWAT model. The basic maps includes the digital elevation model (DEM), soil map, landuse, and land cover. These inputs were used to prepare hydrological response units (HRUs) and to derive various important hydrological parameters relevant to the hydrologic processes of the area. The digital elevation model (DEM) describes the elevation of any point in a given area at a specific spatial resolution. The study used an ASTER Global DEM with an image resolution of 10 meters. The DEM was used to delineate the watershed sub-basins, drainage surfaces, stream network, and longest reaches. The topographic parameters such as terrain slope, channel slope or reach length were also derived from the DEM. The landuse land cover map gives the spatial extent and classification of the various landuse land cover classes of the study area. The LULC data combined with the soil cover data generates the hydrologic characteristics of the basin or for the study area, which in turn determines the excess amounts of precipitation, recharge to the ground water system, and the storage in the soil layers. The LULC data was also used to classify the landuse and land cover type of the study area that are defined within the SWAT 2012 database.

The SWAT model also requires digitized soil map. This was used as the input data for the soils in the user soil database of SWAT to show the spatial distribution of the different types of soils texture of the entire watershed. The soil map used in this study was extracted from the digital soil map of the world (DSMW) with a scale of 1:5000000 and clipped to the extent of the observed watershed. The soils covering the watershed are coded in the global soil database as Nd66-2-3b-4413 (Sandy Loam), Ao109-2-3-4465 (Mountain Soil) and Bg8-2-3a-4478 (Rugao Clay Loam).

Lastly, updated streamflow data obtained from the Bureau of Research and Standards under the Department of Public Works and Highways (DPWH-BRS) was used for the calibration and validation of the model.

SWAT Model Setup

The first step in creating SWAT model input was delineation of the watershed from the DEM. The DEM was used to analyze the drainage patterns of the land surface. Moreover, this also used to determine slope, slope length, channel slope, and length. The watershed delineation process resulted in 26 subbasins. After delineating the watershed using the SWAT model, the HRUs must be determined. The HRUs refer to homogenous areas that represent unique combinations of landuse, soil, and slope. A single HRU can be assigned to each subbasin or multiple HRUs. Subdividing the watershed into areas having unique landuse, soil and slope combinations makes it possible to study the differences in evapotranspiration and other hydrology conditions for different land covers, soils and slopes. To define the distributions of HRUs multiple HRU definition options were tested. Multiple HRUs are determined by sensitivities for the landuse, soil, and slope data specified by the user. The sensitivity or threshold values used were 20% for the landuse class, 10% for the soil class, and 20% for the slope class. This refers to the percentage of the landuse, soil and slope class that covers the subbasin area under which that class is considered negligible and is excluded from the analysis. After overlying the landuse, soil and slope datasets satisfactory the model generated 72 HRUs with a unique combination of landuse, soil, and slope and overlapped 100% with the watershed boundaries.

Moreover, the climate data is one of the main sets of SWAT input for simulating the watershed. Weather inputs consist of daily precipitation, maximum and minimum for the period of 1991 – 2018. Finally, the initial watershed input values have been defined before the SWAT run. These values were set properly based on the watershed delineation, landuse, soil and slope characterization.

Model Performance Evaluation

There are two methods used to measure the model performance or the goodness-of-fit of the model predictions and the model efficiency during the calibration and validation periods. These are the coefficient of determination (R^2) and the Nash Sutcliffe simulation efficiency (NSE). The R^2 is a statistic that gives information about the goodness of fit of a model and ultimately measures how well the regression line approximates the observed streamflow values. The value of R^2 ranges from 0 to 1. The more the value of R^2 approaches 1, the better is the performance of the model and the values of R^2 less than 0.5 indicate a poor performance of the model. The R^2 can be calculated by the following equation:

$$R^2 = \frac{[\Sigma(Q_o - Q_{mo})(Q_s - Q_{ms})]^2}{\Sigma((Q_o - Q_{mo}))^2 (Q_s - Q_{ms})^2} \quad (2)$$

Where, Q_o is the observed streamflow, Q_s is the simulated streamflow, Q_{ms} is the mean of simulated streamflow, and Q_{mo} is the mean of observed streamflow. The general performance rating criteria developed by Sameh, *et al.* (2011) for calibration and validation of SWAT model are given in Table 1.

Table 1. Performance Rating for SWAT using R^2.

Performance Rating	R^2
Very Good	$R^2 > 0.70$
Good	$0.60 < R^2 \leq 0.70$
Satisfactory	$0.50 < R^2 \leq 0.60$
Unsatisfactory	$R^2 < 0.50$

The NSE is the normalized statistics which measures the relative magnitude of the residual variance as compared to measured data variance. Similar to R^2, the more the NSE approaches 1, the better will be the model performance and vice versa. NSE can be calculated by the following equation:

$$\text{NSE} = 1 - \frac{\Sigma(Q_o - Q_s)^2}{\Sigma(Q_o - Q_{mo})^2} \quad (3)$$

Where, Q_o is the observed streamflow, Q_s is the simulated streamflow, and Q_{mo} is the mean of observed streamflow. Performance ratings for NSE of this model are evaluated on different levels due to classification of Saleh, *et al.* (2000) and Bracmort, *et al.* (2006) are given in Table 2.

Table 2. Performance Rating for SWAT using NSE.

Performance Rating	NSE
Very Well	NSE > 0.65
Adequate	0.54< NSE <0.65
Satisfactory	NSE > 0.50

Results and discussion

Sensitivity Analysis Outputs

SWAT sensitivity analysis was done for this study to identify the model parameters that exert the highest influence on model calibration or on model predictions. Initially, a total of fourteen (14) model parameters were used for the sensitivity analysis. Among the 14 model parameters used, eight (8) of them were found to be relatively sensitive. Based on the result of the sensitivity analysis, the curve number (CN2) was found to be the most sensitive parameter with a calibrated value of 77 followed by Base flow alpha factor (ALPHA_BF) with a calibrated value of 0.048, Groundwater delay (GW_DELAY) with a calibrated value of 31, Available water content of soil (SOL_AWC) with a calibrated value of 0.175, Groundwater revap coefficient (GW_REVAP) with a calibrated value of 0.20, USLE practice factor (USLE_P) with a calibrated value of 1 and Soil evaporation compensation factor (ESCO) with a calibrated value of 0.95. On the other hand, the least sensitive model parameter is the threshold depth of water in the shallow aquifer required for return flow to occur (mm H2O) or GWQMN with a calibrated value of 1000. The description of the parameters and their best fitted values used in the SWAT-CUP tool for the considered catchment was presented in Table 3.

SWAT Model Calibration and Validation

In this section, two model evaluation methods were used to assess the performance of the model during the calibration and validation period. To assess the goodness of fit of the model the Coefficient of Determination (R^2) was used and to assess the efficiency of the model performance the Nash-Sutcliffe Efficiency (NSE) method was used. Each calibrated value of the sensitive model parameters were adjusted and changed to identify its individual effect on the simulated streamflow and to fit the model into local condition.

The model was run with the altered combination of different parameter values and after numerous simulations an acceptable calibration results were achieved for monthly streamflow simulations. As a result of the streamflow calibration process, the comparison of observed and simulated flow discharge provides a good result on the coefficient of determination, R^2 value of 0.67 and a satisfactory result on NSE value of positive 0.52. Result of the streamflow validation process also provides a good result with a coefficient of determination, R^2 value of 0.69 and an adequate result on NSE value of positive 0.55. Furthermore, the overall performance of the model was also assessed and evaluated which provide a coefficient of determination, R^2 value of 0.68 and an adequate result on NSE value of positive 0.54. This result indicates that the overall performance of the model in terms of the goodness of fit of the model is good while the overall performance of the model in terms of the efficiency of the model is adequate (Table 4).

Table 3. Calibrated SWAT Model Parameters.

Sensitive Model Parameter	Description	Calibrated Value
CN2	SCS curve number for soil moisture condition	77
ALPHA_BF	Base flow alpha factor	0.048
GW_DELAY	Groundwater delay (days)	31
SOL_AWC	Available soil water content	0.175
GW_REVAP	Groundwater "revap" coefficient	0.20
USLE_P	USLE practice factor	1
ESCO	Soil evaporation compensation factor	0.95
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H2O)	1000

Table 4. Performance of the Model.

Period	Performance of the model			
	R^2	Rating	NSE	Rating
Calibration	0.67	Good	0.52	Satisfactory
Validation	0.69	Good	0.55	Adequate
Overall Performance	0.68	Good	0.54	Adequate

To better analyze the performance of the SWAT model in simulating monthly streamflows, the scatter plots of simulated and observed monthly streamflows during the calibration and validation period are presented in Figs 2.

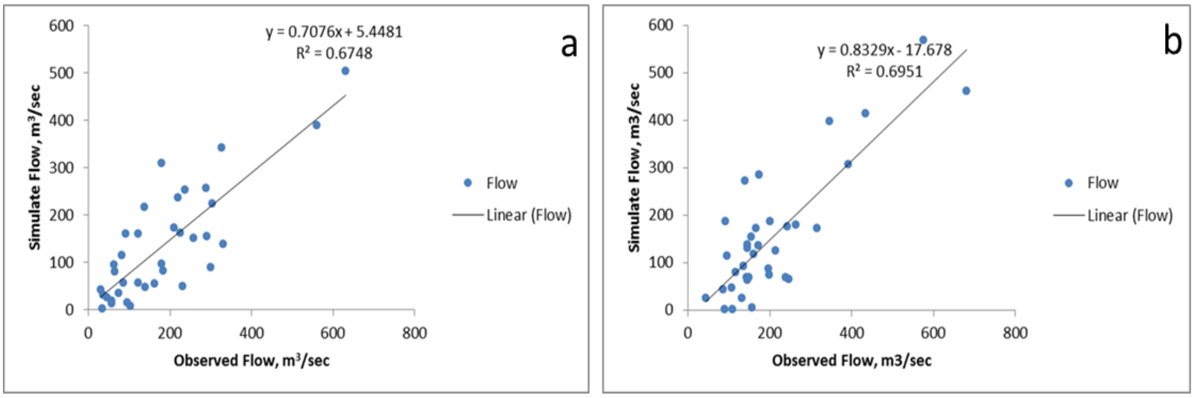

Fig. 2. Scatter plot of the simulated flow vs. observed flow during a) calibration and b) validation period.

Generally, the scatter plot of observed versus simulated flow depicts that the model overestimate some of the low flow and underestimate the high flow. The data points lying above the line of perfect fit shows overestimation while data points below shows some underestimation. Underestimation for the high flow was witnessed due to the result of the unregulated data observations when flow increased moderately at the beginning of the wet season due to early arrival of rain, this resulted an abrupt increase on flow.

On the other hand, overestimation on the discharge during the periods was due to the model's underestimation of ET on water yield, this is due to the observed streamflow data that shows a signature seasonal drop in streamflow as a response to warmer temperatures, more sunlight, and greater evapotranspiration. The closeness of the data points to the line of perfect fit and high value of statistical indices indicate a good performance of the model in estimating streamflow data for the study area. The overall result shows a good linear relationship between the simulated and observed streamflow data during the calibration and validation of the model.

Moreover, the comparison of hydrographs representing simulated and observed streamflow during the calibration and validation period of six (6) years was shown in Fig. 3.

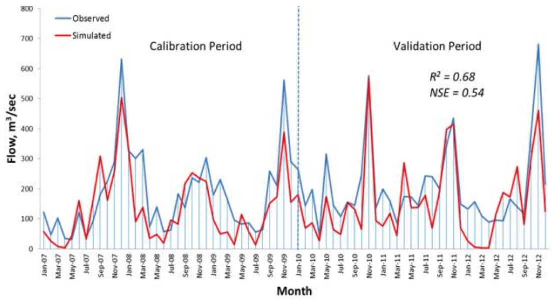

Fig. 3. Monthly observed and simulated streamflow in the study area.

Both simulated and observed discharge was divided into two different periods, the calibration (2007 – 2009) and validation (2010 – 2012) periods. The comparison of monthly simulated and observed discharge indicates that the calibrated SWAT model was poor in predicting low and high streamflow. From 2007 to 2012, underestimation for the high flow during the wet season was observed. The observed data were not paralleled in the modeled results. This can be attributed to the result of the unregulated data observations when flow increased moderately at the beginning of the wet season due to early arrival of rain in the months of May and June, which resulted in an abrupt increase on flows from September to December.

Another discrepancy in the hydrograph is the overprediction of the model on the discharge during the periods. The hydrograph reflects the model's underestimation of ET on water yield as the observed streamflow data shows a signature seasonal drop in streamflow as a response to warmer temperatures, more sunlight, and greater evapotranspiration.

Furthermore, the measured streamflow data of the model also dropped at the start of 2012. This could be attributed to the spatial variability of precipitation, which was not adequately collected by the existing rain gauge.

Lastly, the model evaluation showed good agreement between the observed and simulated streamflow. Based on the overall evaluation result, the performance of the model was good in terms of the goodness of fit of the model using the coefficient of determination or R^2 (0.68), and also adequate in terms of the model efficiency using the Nash Sutcliffe Efficiency or NSE (0.54). The obtained results after calibration and validation of the SWAT model indicate that the hydrologic processes output derived from the model are accurate and reliable. Therefore, this model can be used to simulate other hydrologic processes in the watershed.

Conclusion

For this study, a SWAT model for the Abuan Watershed was set up using required spatial and non-spatial datasets. The model was calibrated and validated by manual fine tuning of the model parameters. During the evaluation, the SWAT model shows underestimation on high flows and overestimation on low flow. This inability of the model to capture peak flows that occur during the wet seasons and low flows occur during dry season were found to be the primary limiting factor for its performance.

Nevertheless, the SWAT model performed well in simulating hydrologic processes within the watershed area. The local model developed shows good agreement between the observed and simulated streamflow values. This results indicates that the hydrologic processes output derived from the local model are accurate and reliable, therefore this local SWAT hydrological model developed is a relevant tool for water resources development and management programs.

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