Controversial Application of SWAT Model to Kurau River Basin, Malaysia

Rasha M. Fadhil[1], Md Kamal Rowshon[2], Koichi Unami[3], Aimrun Wayayok[4], Ahmad Fikri[5]

[1]College of Engineering, University of Mosul, Mosul, Iraq

[1,2,4,5] Faculty of Engineering, Universiti Putra Malaysia, Malaysia

[3]Graduate School of Agriculture, Kyoto University, Japan

Abstract

Minimizing discrepancies between observed and predicted data series is one of the central topics of hydrological process modelling. There are two contrasting approaches of hydrological models: deterministic and stochastic. This paper discusses the controversy over deterministic models, mainly applied to practical problems. The Soil and Water Assessment Tool (SWAT) distributed watershed model hypothesizes the correctness of its model structure representing deterministic physical phenomena. SWAT coupled with Sequential Uncertainty Fitting 2 (SUFI-2) calibration and uncertainty tool, programmed in SWAT Calibration and Uncertainty Procedures (SWAT-CUP). In contrast, one of the stochastic models, is autoregressive with exogenous input (ARX) model with linear Markovian input-output relationship between rainfall and streamflow. Malaysia's Kurau River Basin (KRB) is chosen as a study of predicting streamflow through both mentioned models. Common statistical indicators, coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS), are used for assessing the performance of both models. The outcomes of the sensitivity and uncertainty analysis of parameters using SWAT with SUFI-2 indicate that baseflow and percolation are notified as essential components for total discharge. However, the SWAT-CUP parameters designed for the environment of the North American continent are not suited for all regions. It can be observed that the SWAT model is deficient in capturing the baseflow due to the limitation of its ability to represent groundwater flows rigorously. Furthermore, the SWAT model needs modification to adapt to the peculiar hydrological environment of KRB. The impact of artificial viscosity on flattening and filtering peaks of the streamflow also needs evaluation.

Keywords: ARX, Deterministic model, Statistical indicators, Stochastic model, Streamflow prediction

1. Introduction

Modelling hydrological processes involves discrepancy between observed and predicted data series, and performance of a model is assessed in terms of indices measuring the errors between them. A suitable mathematical model predicts time series fitted to a given observed time series, and the methods to capture the underlying data generating process for the series are referred to as time series analysis. Time series analysis also identifies trends and changes in the series. Understanding the nature of the series in such a way is often useful for prediction of future phenomena. There are two major approaches to development of such hydrological models: deterministic and stochastic. Deterministic models attribute such errors to uncertainty of parameters, while stochastic models deal with the errors inclusively and specifically in their structures. In this paper, we controvert deterministic models especially when applied to practical problems, taking the Soil and Water Assessment Tool as an example (Hasan et al., 2009).

Streamflow prediction is important for water resource planning and management, because it plays a dominant role in many problems such as determination of a reservoir capacity (Kim et al., 2004). Deterministic models assume various potential hydrological scenarios to simulate realistic streamflow variability, provided that considerable attention has been paid for the model structures as well as identification of the model parameters.

SWAT has gained international acceptance as the robust interdisciplinary and useful distributed watershed model designed to predict the streamflow, sediment, water quality, and other parameters. It is applicable to a wide range of water issues with different scales and environmental conditions around the globe (Yesuf et al., 2016). It is also used to model the effect of land management practices and irrigation and agricultural effect on the basin. The principle of prediction by SWAT is to numerically simulate deterministic hydrological processes in the watershed in two phases, a) land use, b) routing stream. This implies that prediction by SWAT is simulation. The land use phase is responsible for the volume of water, sediment, nutrient, and pesticide loadings in each sub-basins to the main channel. The routing stream phase controls the movement of water, sediment through the drainage networks of the watershed to the outlet. Gassman et al. (2007) comprehensively reviewed hundreds of research articles, however, no additional research need was mentioned beyond the scope of simulation. More recent papers still discussed substantially the same points that refinements of SWAT are required. Hülsmann et al. (2015) recommended that SWAT model should be further developed in order to be applicable and transferable to different and critical hydrological conditions and regimes, for instance, melt water from snow and icings for a long time period.

SWAT contains numerous model parameters, and they are difficult to measure directly because of cost, time-consuming and sometimes faced difficulties to achieve it (Zhou et al., 2014). That is leading to focusing on the uncertainty of model parameters, which have significant effects on the simulation results, analysis and decision-making for future planning (Van Griensven et al., 2008). The uncertainty of model parameters is considered as more difficult in assessment and examination comparing with other sources of the errors such as model structures and input data, because the process of parameter identification encounters numerous problems of nonlinearity and ill-posedness. For example, there may be numerous possible solutions through the optimization algorithms (Nandakumar & Mein, 1997). Moreover, different parameter sets may result in similar simulation outputs which is known as the equifinal phenomenon (Beven, 2006). Thus, parameter identification of deterministic hydrological models is simply a difficult task. SWAT is linked with SWAT Calibration and Uncertainty Procedures (SWAT-CUP) tool to quantify the uncertainty of model parameters, embedding different techniques of uncertainty analysis and evaluation such as Generalized Likelihood Uncertainty Estimation (Beven & Binley, 1992), Parameter Solution (ParaSol) (Duan et al., 1992), Bayesian Interface Based On Markov Chain Monte Carlo (MCMC) (Kuczera & Parent, 1998), and Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al., 2004).

SUFI-2 is a semi-automated algorithm to calibrate the hydrological model and represents all sources of errors through parameter uncertainty only (Yang et al., 2008). To achieve high computational efficiency, SUFI-2 algorithm employs sequential runs within uncertainty domains associated with each model parameter, iterating only forward calculations. Application fields of SUFI-2 include streamflow (Setegn et al., 2008), hydrology and the modeling of water quality (Abbaspour et al., 2007), sediment load (Talebizadeh et al., 2010), and freshwater availability (Schuol et al., 2008). In other words, the large number of SUFI-2 users in recent years neglect or do not notice the sources of errors stemming from model structures or input data. Nevertheless, there are some points mentioned from other studies. Ning et al. (2015) referred to the difficulties of determining the spatial locations of the non-spatial aspects of HRUs and describing the interactions between different HRUs. Krishnan et al. (2018) illustrated that the probability distribution of parameters is assumed uniform, which may not always be correct.

Therefore, this study examines advantages of stochastic models to represent input-output relationship between weather data and streamflow, including the errors between observed and estimated streamflow time series in the model structure. According to (Yeh, 1985), a simple stochastic model may yield better prediction of hydrological time series than a more complex deterministic model. Furthermore, hydrological time series are non-deterministic in nature and therefore cannot be predicted with certainty for future. Stochastic models are preferred also in this context as the probability limits for prediction may readily be obtained. Even though a stochastic model can be either linear or nonlinear, considering probability distributions of errors makes it possible that a linear stochastic model describes the complexity of time series in the real world (Lohani et al., 2012). As a result, linear stochastic models have drawn much attention due to their relative simplicity in understanding and implementation (Unami & Kawachi, 2005). Among such linear stochastic models, a linear autoregressive with exogenous input (ARX) model is employed here, in order to consider the effect of rainfall as exogenous input on streamflow having autoregressive properties.

Finally, SWAT integrated with the process of SUFI-2 fitting is compared with ARX in the context of application to Kurau River Basin (KRB), Malaysia. A gridded metrological data using kriging and inverse distance interpolation techniques are used for reconstruction of distributed weather data (Wong et al., 2011). Prediction of the streamflow in KRB is important because it is the dominant inflow into the Bukit Merah Reservoir (BMR) serving as the primary water source of the Kerian Irrigation Scheme (Bobbio & Trivedi, 1986). Results of prediction can be beneficial for supporting decision making in optimal operation and management of a reservoir and its watershed under the conditions of rapid increasing industrial development, anthropogenic activities, irrigation demands, and the climate change in general, especially in this era of information and communication technology (Mahmoud et al., 2016; Park et al., 2014). However, it is another weakness of SWAT model that its prediction is limited to simulation without considering feedback of observed streamflow which shall be incorporated in real-time operation of the reservoir and water allocation for different users.

2. Materials and Methods

2.1 Outline of SWAT

SWAT is a physically based river basin model developed by United States Department of Agriculture-Agriculture Research Service (USDA-SCS, 1986), considering semi-distributed transport processes in watersheds with a specified time-step. SWAT has been developed by Arnold et al. (1998) to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds with different soils, land-use, and management conditions over long periods of time (Winchell et al., 2007). The model is composed of eight major components including hydrology, weather, sedimentation, soil moisture, crop growth, nutrients, agricultural management, and pesticides. SWAT offers spatial details of watershed through the water balance accounting for each sub-basin and hydrologic response unit (Tangang et al., 2007). The watershed is divided into several smaller units called sub-basins where the land use phase dominates. The sub-basins are further divided into homogenous standardized HRUs characterized by uniform soil-land use and slope representing a unique hydrologic response (Eckhardt & Arnold, 2001). The water dynamics over each HRU is estimated in the context of the mass balance equation

$$V_{t+1} = V_t + R_t a - Q_{surf} - Ea - Q_{perc} - Q_{gw} \tag{1}$$

where V_t is the soil water content in the HRU at the beginning of the t th time step, R_t is the rainfall depth on the t th time step, Q_{surf} is the balance of surface runoff volume on the t th time step, E is the evapotranspiration depth on the t th time step, Q_{perc} is the volume of deep percolation on the t th time step, Q_{gw} is the balance of hirizontal growndwater flow on the t th time step, a is the area of the HRU, and the time steps may be of daily, monthly, or annual base, depending on the magnitude of basin (Arnold et al., 2012). The surface daily discharge is estimated using the Soil Conservation Service (SCS) curve number method. Evapotranspiration is also computed using either the Hargreaves, Priestley-Taylor or the Penman-Monteith methods. The water dynamics in the HRUs aggregates for the entire basin to drive the routing stream phase. In SWAT, water flow is routed through the channel network using the variable storage or the Muskingum routing methods. The storage volume in Muskingum routing is a variable defined on each reach of the channel network, assuming that it is a linear combination of the inflow rate I_t and the outflow rate O_t in the reach on the t th time step with a weighting factor which may depend on the celerity. Applying the central difference scheme in the temporal domain, the Muskingum routing is written in the form of:

$$O_{t+1} = C_0 I_{t+1} + C_1 I_t + C_2 O_t \tag{2}$$

where the coefficients C_0, C_1, and C_2 are automatically adjusted from the celerity and spatio-temporal grid sizes, and I_{t+1} is given as a result of the land use phase. Finally, SWAT gives simulation outputs at each sub-basin and the whole basin along with discharges at outlets specified by user.

2.2 Outline of ARX

ARX is applied in current study for comparing with nonlinear deterministic model represented by SWAT. We assume a linear Markovian input-output relationship between rainfall and streamflow with an offset Δ. Then, discrete time series with a length n of observed rainfall R_t and observed streamflow Q_t ($0 \le i < n$) are related as:

$$z_{p+i} = \sum_{k=0}^{p-1} \left(K_{p-1-k} z_{k+i} + K_{2p-1-k} R_{k+i} \right) + e_{p+i} \tag{3}$$

$$z_{p+i} = Q_{p+i} + \Delta \tag{4}$$

where p is the order representing the number of lagged time steps ($0 < p < n$), K_k ($0 \le k < 2p$) are model coefficients, and e_{p+i} ($0 \le i < n-p$) are errors. Substituting Eq. 4 into Eq. 3 results in

$$Q_{p+i} = \sum_{k=0}^{p-1} \left(K_{p-1-k} Q_{k+i} + K_{2p-1-k} R_{k+i} \right) + \left(\sum_{k=0}^{p-1} K_{p-1-k} - 1 \right) \Delta + e_{p+i} \tag{5}$$

for $0 \le i < n-p$, which comprise a linear equations system

$$\begin{pmatrix} Q_p \\ \vdots \\ Q_{p+i} \\ \vdots \\ Q_{n-1} \end{pmatrix} = \begin{pmatrix} Q_{p-1} & \cdots & Q_0 & R_{p-1} & \cdots & R_0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ Q_{p-1+i} & \cdots & Q_i & R_{p-1+i} & \cdots & R_i & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ Q_{n-2} & \cdots & Q_{n-p-1} & R_{n-2} & \cdots & R_{n-p-1} & 1 \end{pmatrix} \begin{pmatrix} K_0 \\ \vdots \\ K_{p-1} \\ \vdots \\ K_{2p-1} \\ c \end{pmatrix} + \begin{pmatrix} e_p \\ \vdots \\ e_{p+i} \\ \vdots \\ e_{n-1} \end{pmatrix} \tag{6}$$

with $c = \left(\sum_{k=0}^{p-1} K_{p-1-k} - 1 \right) \Delta$, and abbreviated as

$$\mathbf{Q} = X\mathbf{K} + \mathbf{e}. \tag{7}$$

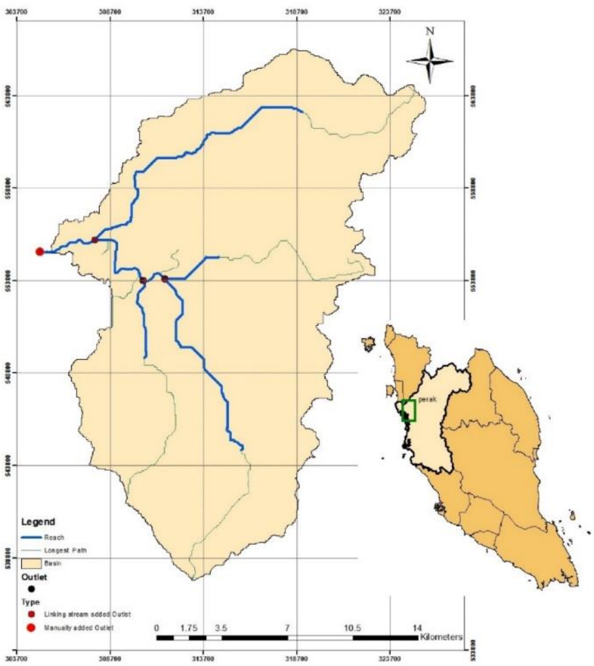
Assuming that the vector $\mathbf{K}$ of model coefficients is time invariant with the statistically equilibrium error vector $\mathbf{e}$, the square norm $\sqrt{\mathbf{e}^T \mathbf{e}}$ of $\mathbf{e}$ is minimized by the least square method computing $\mathbf{K}$ as

$$\mathbf{K} = \left(X^T X \right)^{-1} X^T \mathbf{Q}. \tag{8}$$

2.3 Description of study area

BMR, constructed in the year 1906 in the Northwest of Perak State, Malaysia, is an important water source for KIS, which is one of the country's eight largest granaries with net paddy area of 235.6 km^2. The total catchment area of BMR is 682 km^2. KIS receives about 61% of the irrigation water demand from BMR and the rest from rainfall. Furthermore, BMR provides fresh water to achieve the domestic and industrial demands to Kerian District as well as Larut Matang District. The Kurau River is the largest of the streams filling BMR. Located between 04° 51′ N and 05° 10′ N latitude and 100° 38′ E to 101° 01′ E longitude, the Kurau River Basin (KRB) having an area of 322 km^2 represents the main drainage artery of the basin pouring into BMR. KRB has two tributaries of Ara and Kurau rivers with confluence at Pondok Tanjung town (Ismail & Najib, 2011). Fig. 1 delineates KRB and its river system. The land utilization comprises of forestry 46% and agriculture 43% and 50% of the land and privately owned by individual farmers, which makes it tough to implement sound land-use policies of management for this watershed. Both the natural and human factors influence the streamflow, which can respond quickly to changes in the flow parameters. The weather has a significant impact on the streamflow; it increases after rainstorms and decreases during dry periods, as well as evaporation and water use in plants, affects significantly in the streamflow. It is also affected by the subsurface water flow. The changes in seasonal streamflow, coupled with increased requirement for demands because of growing population, place significant pressure on the efficient management of available water resources. It is true especially during dry spells when streamflow is limited and water requirements are considerably high. To avoid the critical conditions of water deficiency for the intended users, prediction of streamflow for the long term might be helpful to ensure the availability of adequate quality and quantity of water in anytime. However, the calibration of the prediction model for the watershed is a challenging task due to the uncertainty of the hydrological elements.

Figure 1: Kurau River Basin and its river system in Peninsular Malaysia



2.4 Datasets

In SWAT, the hydrological process depends on the relevant parameters, which are driven by ArcSWAT model. Spatial and meteorological datasets are used for this purpose and also for calibration and validation processes. Spatial data sets such as Digital Elevation Model (Malaysia, 2010), land use/land cover, and soil properties map are used to represent hydrological behavior governing the system. The DEM in raster format with a cell size of 30m×30m grid was provided by Department of Irrigation and Drainage office (DID, 2011), with SRTM spatial reference data: kertau-RSO-Malaya-meters. DEM makes the conception of flow patterns and behaviors easy in understanding the processes of generation slope and drainage outlet points for the watershed. Furthermore, DEM plays key role in fast and slow runoff processes (Narsimlu et al., 2015; Patel & Srivastava, 2013).

Next, land use land cover (LULC) parameters were obtained from Department of Agriculture (DOA) office. LULC parameters are the most important factor for understanding hydrological processes on the watershed and evaluating the ability to save catchment from environmental processes such as soil erosion and runoff. It has classified into nine classes through ArcCatalog, and all of the categories have been reclassified using SWAT Geodatabase categories shown in Fig. 2. There are six classes for the soils including Forest-Deciduous, Forest-Mixed, Garrigue, Oil Palm, Orchard, and Agricultural Land-Generic as presented in Tab. 1.

Table 1 : Characteristics of land use, soil type, and slope in KRB

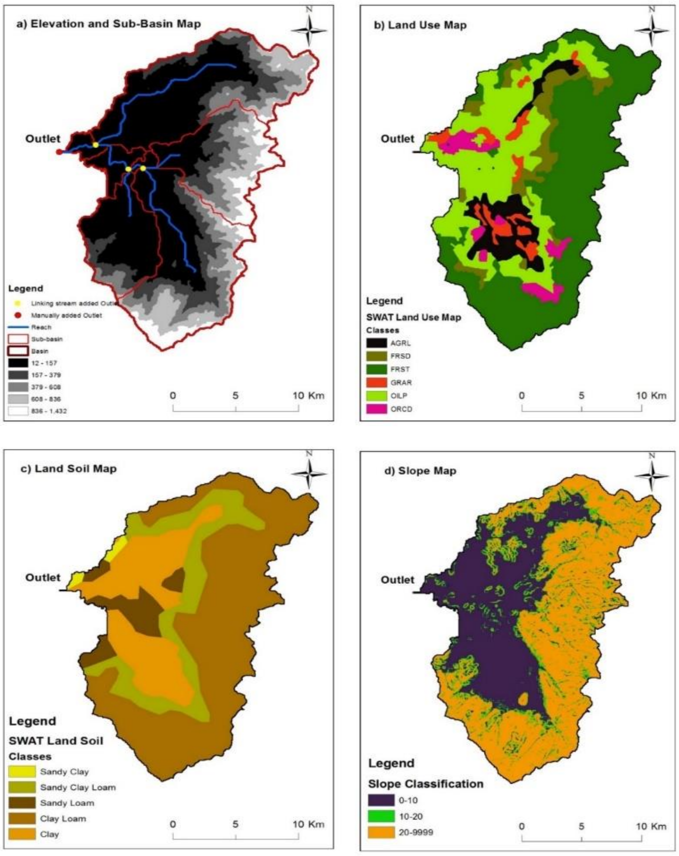
Parameters	Characteristics	Area (ha) Total = 32260.7	Percentage
LANDUSE	Forest-Deciduous --> FRSD	2294.5	7.1
	Forest-Mixed --> FRST	15965.9	49.5
	Garrigue --> GRAR	1011.7	3.1
	Oil Palm --> OILP	9757.4	30.2
	Orchard --> ORCD	1101.1	3.4
	Agricultural Land-Generic --> AGRL	2130.1	6.6
SOIL	Sandy Clay	229.7	0.7
	Sandy Clay Loam	5266.7	16.3
	Sandy Loam	18193.8	56.4
	Clay Loam	6322.2	19.6
	Clay	2248.2	7.0
SLOPE	0-10	10877.6	33.7
	10-20	3546.3	11.0
	20-9999	17836.8	55.3

The last SWAT model requirement for spatial datasets is different soil textural and physicochemical properties such as soil texture, water content, hydraulic conductivity, bulk density, and organic carbon content information for various layers. The soil map was obtained from the DID office in jpeg format and digitized into shapefile format. The soil parameters are characterized into seven groups according to SWAT model Geodatabase shown in Fig. 2. The main soil categories in KRB are reported in Tab. 1. The most of them fall under soil groups B and C of the hydrological soil classification.

A collection of high quality datasets is essential means for applications in hydrologic model, especially with increasing concern of global resource availability and hydrological extreme events and their impacts in management and planning of rivers basins. However, due to lack of sufficient historical data in many catchments, interpolated gridded datasets over space and time are becoming increasingly important in hydrological modeling studies such as model calibration and validation purposes.

Daily weather data of rainfall, maximum temperature ($T_{\max}$), and minimum temperature ($T_{\min}$) are available for the period 1976-2006 at four stations, and kriging and inverse distance interpolation techniques (Wong et al., 2011) refine those data into 0.05° by 0.05° spatial resolution to be used in SWAT. Daily streamflow records observed at the station No. 15007421 in KRB for that period were obtained from the DID. The weather daily data are commonly used for model calibration and validation.

Figure 2: Spatial input data to SWAT model for KRB, including (a) Digital elevation model (DEM) of 30m resolution and sub-basins partitioning, (b) Reclassified land-use raster data, (c) Soils data from Department of Agriculture (DOA), and (d) Slope map



2.5 Assessment of prediction

The coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS) are used for assessing the performance of SWAT and ARX in streamflow prediction.

The statistical indicator R^2 is widely used in hydrological model studies to measure the strength of the linear correlation between observed and predicted time series, describing the proportion of the variance in measured data explained by the model. The value of R^2 is calculated with

$$R^2 = \frac{\left(\sum_{i=1}^{n} (Q_i - Q')(P_i - P') \right)^2}{\sum_{i=1}^{n} (Q_i - Q')^2 \sum_{i=1}^{n} (P_i - P')^2} \tag{9}$$

where Q_i and P_i are the observed and the predicted discharges of streamflow in the ith day, respectively, Q' and P' are the averages of Q_i and P_i, respectively, and n is the length of data series. The value of R^2 varies between 0 and 1. When R^2 is equal to unity, it indicates a perfect positive correlation between Q_i and P_i, and normally any value more than 0.5 is considered acceptable. On the other hand, R^2 vanishes when there is no correlation at all between the Q_i and P_i. To reach a good agreement, the intercept should be close to zero and the gradient should be close to one (Kuczera & Parent, 1998). Nash-Sutcliffe Efficiency (NSE) is another most popular statistical indicator used for assessing the predictive power of hydrological models. It normalizes the residual error between observed and predicted time series against the mean observation. NSE is defined as

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (Q_i - P_i)^2}{\sum_{i=1}^{n} (Q_i - Q')^2} \tag{10}$$

and ranges from $-\infty$ to 1. When NSE is equal to unity, it indicates a perfect match between Q_i and P_i, while vanishing NSE indicates that the accuracy of model prediction is at a level of taking the mean of observed data series. A negative value of NSE indicates poor performance as the residual variance is larger than the data variance, implying that observed mean is a better predictor than the model. To sum, the closer NSE is to 1, the more accurate the model. Percent Bias (PBIAS) measures the mean tendency of predicted data series; it reveals whether the model gives larger or smaller values than their observed counterparts (Gupta et al., 1999), using the calculation formula

$$\text{PBIAS} = 100 \frac{\sum_{i=1}^{n} (Q_i - P_i)}{\sum_{i=1}^{n} Q_i}. \tag{11}$$

Values of PBIAS indicate the average deviation of model prediction from the observation. Positive and negative PBIAS values indicate underestimation and overestimation, respectively. Provided that R^2 and NSE indicate a good performance of the model, a small absolute value of PBIAS means that the model is accurate.

2.6 Implementation of SWAT

SWAT interfaces with ArcGIS product for hydrological analysis. The DEM of KRB was loaded to ArcSWAT for topographic analysis, automatically delineating a basin into sub-basins. A predefined digital stream network layer was imported and covered onto the DEM for accurately delineating of the streams' location.

Definition of HRUs followed the sub-basins discretization. HRUs overly look up tables which were created previously to recognize the SWAT code for the different categories of land use on the map format. Further, the soil map was linked with the soil database which holds data for soils worldwide. The entire watershed was classified into 3 slope categories depending on the watershed topography. For multiple HRU definition, land uses, soils, and slope categories that cover less than threshold levels of sub-basins areas are eliminated. ArcSWAT user's manual suggests that reasonable threshold levels for most applications are a 20 percent for land use and slope, a 10 percent for soil. Subsequently the elimination processes the area of the land use, soil or slope is reallocated to create 100 percent of them included in the actual implementation of SWAT. Tab. 1 contains information related to hydrologic characteristics of relevant land use, soils and slope (Setegn et al., 2008).

After that, all input files for daily weather generator data (from WGEN-User) and weather stations for rainfall, $T_{\max}$ and $T_{\min}$ (through look up tables) were prepared to start simulation of streamflow at outlet gaging station 1. SWAT has ability to generate missing values of hydrological data, based on the completed files of meteorological datasets. Along with this, estimating evapotranspiration establishes the water balance of each HRU. Finally, the simulation module for KRB was obtained, so that calibration and uncertainty sensitivity analysis for the model will be done using SUFI-2 Algorithm.

2.7 Statistical evaluation of SWAT simulations

SWAT-CUP program is a public domain calibration tool linked with SWAT through the genetic interface. It is based on Latin Hypercube and One factor-At-a-Time (LH-OAT) sampling for sensitivity analysis and sequential uncertainty fitting algorithm (Schuol et al., 2008) for calibration of outputs from SWAT. SUFI-2 is a semi-automated inverse analysis program based on a Bayesian algorithm, having high efficiency in calculating optimal results against analyzing a large number of spatially heterogeneous parameters in the smallest number of iterations (Yang et al., 2008).

Conducting Latin hypercube sampling, the model parameters are optimized to achieve the best values of the three indices (R^2, NSE, and PBIAS). The notion of sensitivity and uncertainty in model parameters is indispensable to appropriate understanding of the calibration results. SWAT-CUP assumes uniform distribution of each model parameter within an uncertainty band. An envelope of streamflow data series bounded by 2.5 % and 97.5 % cumulative distribution of Latin hypercube sampling is referred to as by 95 percent prediction uncertainty (95PPU). Then, the SWAT simulations are evaluated in terms of statistics. For sensitivity analysis, statistical tests are conducted with *t*-stat and *p*-value. The value of *t*-stat represents the magnitude of sensitivity to the objective functions, while *p*-value determines the significance of sensitivity.

Abbaspour et al. (2007) employed two indicators; *p*-factor and *r*-factor, which provide a measure of the model's efficiency to capture uncertainties and measure the calibration quality, respectively. Those factors are defined as

$$p\text{-factor} = \frac{1}{n}\sum_{i=1}^{n}\chi_{Q_i \in \left(P^M_{i,2.5\%}, P^M_{i,97.5\%}\right)} \tag{12}$$

where $P^M_{i,97.5\%}$ is the upper bound of 95PPU at the *i*th step, $P^M_{i,2.5\%}$ is the lower bound of 95PPU at the *i*th step, and χ is the indicator function, and

$$r\text{-factor} = \frac{1}{n\sigma_Q}\sum_{i=1}^{n}(P^M_{i,97.5\%} - P^M_{i,2.5\%}) \tag{13}$$

where σ_Q is the standard deviation of the observed streamflow, respectively. The value of *p*-factor ranges between 0 and 1, and the latter is an ideal value meaning 100 % bracketing of observed data series and consequently accounting for all the correct processes. On the other hand, *r*-factor can take any non-negative value and ideally should be near to zero.

3. Results and Discussion

Daily streamflow data from the KRB station divided into two sets; 4 years (1991-1994) and 1 years (1998) for calibration and validation periods, respectively. In SWAT, the preceding 5 years and 3 years were considered for the model warm-up period for calibration and for validation, respectively. ARX uses the rainfall at station 1 as R_t, because the time series has the least missing data, which have been linearly interpolated. The calibrated ARX generates two types of time series: estimated and simulated streamflow. ARX estimated stream flow Q^E_{p+i} is generated as

$$Q^E_{p+i} = \sum_{k=0}^{p-1}\left(K_{p-1-k}Q_{k+i} + K_{2p-1-k}R_{k+i}\right) + c \tag{14}$$

while ARX simulated stream flow Q^S_{p+i} is generated as

$$Q^S_{p+i} = \sum_{k=0}^{p-1}\left(K_{p-1-k}Q^S_{k+i} + K_{2p-1-k}R_{k+i}\right) + c \tag{15}$$

with $Q^S_i = Q_i$ for $0 \le i < p$.

3.1 Calibration and sensitivity analysis

The limited and effective number of model parameters that have more influence in simulating streamflow were used in calculating hydrological component for SWAT sensitivity analysis, some of which were taken from relevant literature (Lenhart et al., 2002). 500 runs were executed to achieve a good fit efficiency between observed and simulated streamflow time series, and the fitted parameters with the highest sensitivity were used to assess the model performance with *t*-stat and *p*-value. A larger absolute value of *t*-stat represents high sensitivity, while a *p*-value close to zero implies that the model parameter is more siginificant. The most critical 14 model parameters that influence the streamflow behavior are summarized in Tab. 2. Based on the results of statistical sensitivity analysis, the most critical model parameters are:

Saturated hydraulic conductivity (SOL_K), Groundwater delay (GW_DELAY), Effective hydraulic conductivity in main channel alluvium (CH_K2), and Baseflow alpha factor (ALPHA_BF). The uncertainty in terms of *p*-factor was 0.58, and the band region in terms of *r*-factor was 0.80. There is no balance between two values in achieving a large value of *p*-factor at the expense of a smaller *r*-factor (Abbaspour, 2011). A number of factors could be contributing on unbalance estimating of *p*-factor and *r*-factor, including errors in observation data, deficiency of model structure, and the subjectivity associated with the SUFI-2 procedure. The present analysis only focuses on parameters' uncertainty. KRB has large variations in topography, precipitation, land use, and soil type, with high variability in rainfall depths during the monsoon and non-monsoon periods. It could be the main contribution in increasing uncertainty issues in the input weather data within the region because of insufficient data availability, especially at the micro level (Yadav et al., 2014). Another source of uncertainty could arise as a result of using modified interpolated data introduced by Wong et al. (2011) since elevation not considered during the interpolation process. The weather interpolation data in sub-basins was calculated depending on the nearest weather stations that may not represent real weather conditions at the station level. Even in the catchment with dense rain gauges, the state of uncertainty still exists in the transfer of precipitation to the value for the site area (McMillan et al., 2011). They highlighted the further studies on the structure of the model and input data on the uncertainty analysis.

Table 2 : Calibration and sensitivity analysis for SWAT model parameters

No.	Parameters name	Definition	Min-range	Max-range	Fitted value	*T*-stat	*P*-value
1	V__ALPHA_BF.gw	Baseflow alpha factor	0	1	0.513	1.835	0.086
2	V__GW_DELAY.gw	Groundwater delay	0	500	12.36	-2.59	0.020
3	V__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	0	10000	4998.69	-0.805	0.433
4	V__GW_REVAP.gw	Groundwater "revap" coefficient	0.02	1	0.26	0.233	0.819
5	V__REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur	0	500	4.77	-0.043	0.966
6	V__GWHT.gw	Initial groundwater height	0	25	0.872	−0.875	0.395
7	R__CN2.mgt	SCS runoff curve number	−5	105	-0.739	−0.14	0.88

8	V__EPCO.hru	Plant uptake compensation factor	0	1	0.237	0.330	0.746
9	V__ESCO.hru	Soil evaporation compensation factor	0	1	0.137	−0.25	0.806
10	V__CANMX.hru	Maximum canopy storage	0	100	53.07	0.906	0.379
11	R__SLSUBBSN.hru	Average slope length	0.1	150	0.782	−0.846	0.410
12	R__SOL_AWC .sol	Available water capacity of the soil layer	0	1	0.092	−0.805	0.433
13	R__SOL_K .sol	Saturated hydraulic conductivity	0	2000	38.87	3.178	0.006
14	V__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/hr)	−0.01	500	193.10	2.510	0.0239

Calibration of ARX is to constructed X and $\mathbf{Q}$ from the observed data series and then to solve Eq. 8. Although a systematic method such as AIC was not used, different values are tested to determine the order p of ARX. As a result, it turned out that the order p of ARX can be taken as small as 6, contradicting the groundwater delay of 12.36 days as a SWAT model parameter. The ARX model coefficients K_k for $p = 6$ are shown in Tab. 3, and the offset Δ is equal to 0.0034. Taking p as 7, 14, 28, 120, and 360 results in similar consequence that the streamflow depends mostly on the streamflow the day before and the rainfall in the preceding 6 days.

Table 3: Calibration results for ARX model coefficients

K_0	K_1	K_2	K_3	K_4	K_5	K_{6+0}	K_{6+1}	K_{6+2}	K_{6+3}	K_{6+4}	K_{6+5}
0.5758	−0.0410	0.0773	0.0971	0.0504	0.0274	0.0316	0.0137	0.0465	0.1982	0.2384	0.0427

Observed and predicted streamflows during the calibration period from 1991 to 1994 are compared in Fig. 3, which shows 95PPU bands (upper and lower band) and the rainfalls at the four stations as well. The average of the observed specific discharge of streamflow during this calibration period is 17.08 mm/day. As can be seen from Fig. 3, SWAT is unable to capture the observed streamflow in terms of 95PPU during critical periods of floods and droughts. ARX estimated streamflow reasonably follows the observed streamflow. The ARX simulated streamflow departs from the observed streamflow at almost similar level as the SWAT simulated streamflow does. To make more quantitative comparison, the statistical indicators (R^2, NSE and PBIAS) for SWAT simulated, ARX estimated, and ARX simulated streamflows are summarized in Tab. 4, which includes the results of validation discussed later as well. For simulation, SWAT shows a better performance than ARX in terms of R^2 and NSE but tends to underestimate as PBIAS is negative. An advantage of ARX simulated streamflow is that it can provide statistical information of the errors, rather than the higher values of R^2 and NSE. Its PBIAS is equal to 0 as a property of the least square method employed. Fitting a probability distribution to the errors between the ARX simulated and observed streamflows is out of scope of this study, however, it will contribute to construct more sophisticated prediction or control models.

Figure 3: Observed and predicted streamflows during the calibration period with 95PPU

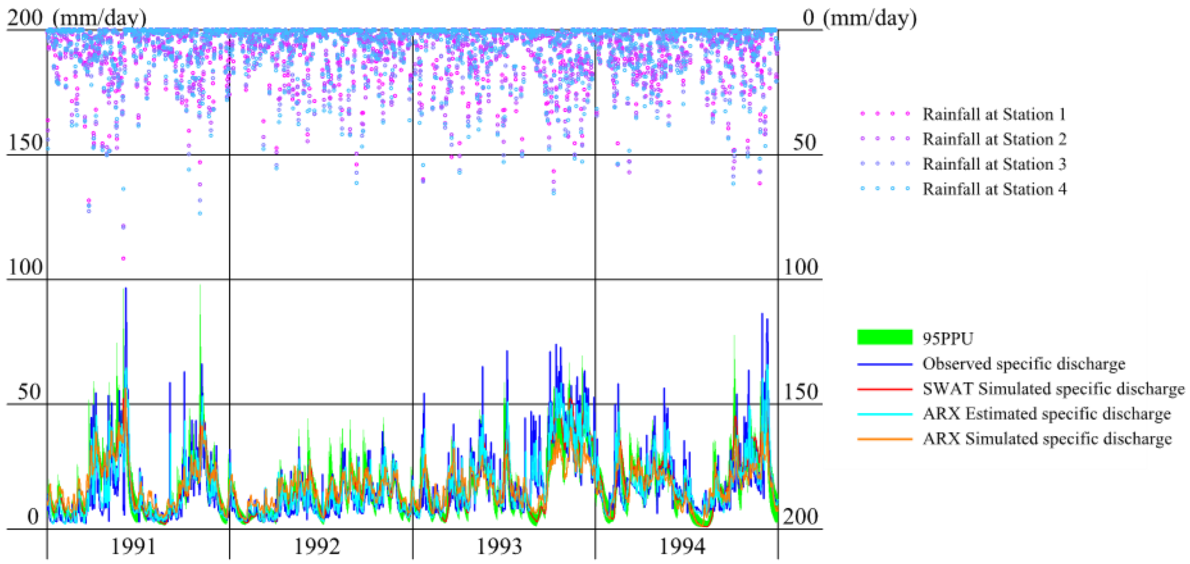


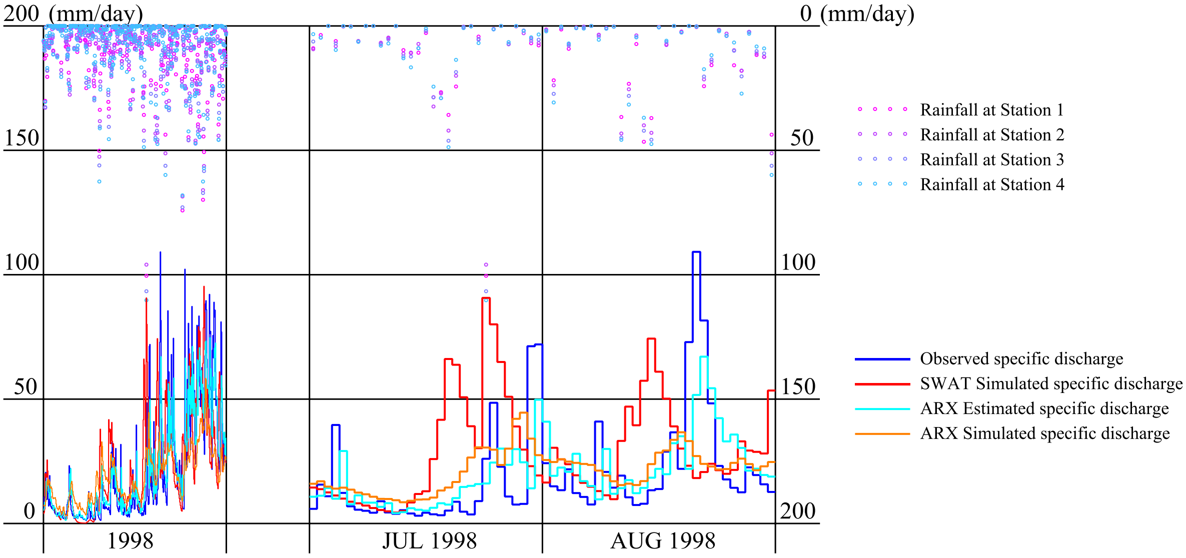
Table 4: Statistical indicators of streamflow predictions during calibration and validation periods

	Calibration (1991-1994)			Validation (1998)		
	SWAT simulated	ARX estimated	ARX simulated	SWAT simulated	ARX estimated	ARX simulated
Average	17.77	17.08	17.11	22.42	21.33	19.26
R^2	0.56	0.71	0.47	0.32	0.75	0.58
NSE	0.55	0.71	0.47	0.25	0.74	0.50
PBIAS	−1.5	−0.00	−0.15	−2.3	2.7	12

3.2 Streamflow prediction with validation

Validation is performed with the model parameters which have been fixed as a result of calibration. Accordingly, there is no 95PPU bands, and thus *p*-factor and *r*-factor become zero. Observed and predicted streamflows during the validation period (Allen et al., 1998) are compared in Fig. 4, with a close up for July and August months where both extremes of flood and drought appear. The average of the observed specific discharge of streamflow during this validation period is 21.92. Performance of SWAT deteriorates in validation so much that R^2 and NSE for SWAT simulated streamflow become less those for ARX simulated streamflow even. PBIAS values indicate that holistic bias of SWAT simulated streamflow is less, however, PBIAS cannot evaluate incorrect reproduction of the extreme events typically occurred in July and August months of 1998: peaks and bottoms are simulated on wrong days. This is a well-known defect of SWAT (Tolson & Shoemaker, 2007).

Figure 4: Observed and predicted streamflows during the validation period



3.3 Controversy over SWAT

The outcomes of the sensitivity and uncertainty analysis of parameters using SWAT with SUFI-2 indicate that baseflow and percolation are notified as important components and responsible for total discharge at the given outlet in the study area that contributes are significantly higher than the surface runoff. The high fitted value of GWQMN, the depth of water required for return flow to occur in shallow aquifer, is 4998.7 mm, which is very close to the maximum boundary that SWAT specifies. A delay of 12.36 days is estimated for recharge of the shallow aquifer depending on the depth to water table and hydraulic conductivity, indicating that the aquifer in KRB is so thick to increase the chance of contributed return flow to provide streamflow. The high value of CH-K2 (193.1 mm/hr) implies that the stream located in a recharge area is influent stream receiving water from groundwater flow (Lane, 1983). However, the SWAT-CUP parameters designed for USA environment are not suited for all regions such as South-East Asia in particular. To sum, it can be observed that the model is deficient in capturing the baseflow due to the limitation of SWAT ability to rigorously represent groundwater flows. On the other hand, the fitted value of CN2, the SCS runoff curve number, is as low as 0.5, implying that the surface runoff is almost non-existent. In fact, the default range of CN2 is 35-98, which does not achieve any physically meaningful result, and thus it has been modified to adapt the peculiar hydrological environment of KRB. The routing stream phase of SWAT is challenged in the context of computational fluid dynamics. Provided that the grid sizes satisfy certain stability conditions, SWAT maintains numerical stability and avoids the computation of negative values. However, as the celerity is based on the assumption of kinematic wave, modelling errors are unavoidable when the friction force is not dominant in the streamflow. SWAT is also unable to evaluate the effects of artificial viscosity on flattening and filtering peaks of the streamflow.

4. Conclusion

Prediction of hydrological streamflow requires a strong calibration model to obtain effective model parameters as well as rigorous uncertainty analysis for application to practical problems. In this study, SWAT and ARX have been applied to KRB for calibration in the period from 1991 through 1994 by following the calibration technique using SUFI-2 and the least square method, respectively. The common use of SUFI-2 algorithm is for estimating the sensitivity and uncertainty of a hydrological model parameters, supported by an effective graphical interface for visualizing outputs, containing predicted data, observed data, best-fit model of results and 95PPU for all variables contributed in the calibration model. The sensitivity analysis adopted for streamflow calibration shows the dominant variations in the efficacy of the parameters ranges, that are configured to calibrate the model on a daily scale according to Latin hypercube sampling systems. Then the models have been validated in the period of 1998.

After the processes of calibration and validation, controversy over SWAT has been revealed. SWAT hypothesizes correctness of its model structure representing deterministic physical phenomena and therefore is unable to deal with contradictions as mentioned. Applicability of SWAT to assessing the effect of land use management, which is supposed to be the main advantage of SWAT, shall be critically examined as well.

A major advantage of stochastic models such as ARX is to generate synthetic streamflow time series that are statistically similar to observed streamflow time series. Statistical similarity implies that the generated and observed time series have similar statistics and dependence properties. Such time series represent plausible future streamflow scenarios under the assumption that the future statistical properties will be similar to the past. Moreover, stochastic models are assured in dealing with predicting streamflow when incorporated in feedback control systems, on which deterministic models cannot operate. This will be an advantage of ARX applied to management of BMR receiving streamflow of KRB.

Acknowledgment

The authors wish to acknowledge the Ministry of Higher Education in Iraq and Mosul University, Mosul, Iraq for providing the scholarship. The authors would like to thank also the Ministry of Higher Education in Malaysia (MOHE) and Universiti Putra Malaysia for providing funding for this research. This research is funded by Putra Grant No. 9406300 from the Universiti Putra Malaysia and Grants-in-Aid for Scientific Research Nos. 26257415, 16KT0018, and 16K15007 from the Japan Society for the Promotion of Science (JSPS). We are grateful to the staff of the Department of Irrigation and Drainage (DID), Department of Agriculture (DOA) and the National Hydraulic Research Institute of Malaysia (NAHRIM) for providing spatial and hydro-meteorological data.

References

Abbaspour, K. C., Johnson, C. A., & Van Genuchten, M. T. (2004). Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone Journal, 3*(4), 1340-1352.

Abbaspour, K. C. (2011). SWAT-CUP4: SWAT calibration and uncertainty programs–a user manual. *Swiss Federal Institute of Aquatic Science and Technology, Eawag*.

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., & Srinivasan, R. (2007). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology, 333*(2-4), 413-430.

Allen, G, R., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. *FAO, Rome, 300*(9), D05109.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R., Van Griensven, A., & Van Liew, M. W. (2012). SWAT: Model use, calibration, and validation. *Transactions of the ASABE, 55*(4), 1491-1508.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). Large area hydrologic modeling and assessment - Part 1: Model development. *Journal of the American Water Resources Association, 34*(1), 73-89.

Beven, K. (2006). A manifesto for the equifinality thesis. *Journal of Hydrology, 320*(1), 18-36.

Beven, K., & Binley, A. (1992). The future of distributed models: model calibration and uncertainty prediction. *Hydrological Processes*, *6*(3), 279-298.

Bobbio, A., & Trivedi, K. S. (1986). An aggregation technique for the transient analysis of stiff Markov chains. *Computers, IEEE Transactions on, 100*(9), 803-814.

DID. (2011). *Review of the national water resources study (2000-2050) and formulation of national water resources policy: final report*. Kementerian Sumber Asli Dan Alam Sekitar Malaysia.

https://www.water.gov.my/jps/resources/PDF/Hydrology%20Publication/Vol2WaterGovernance.pdf

Duan, Q., Sorooshian, S., & Gupta, V. (1992). Effective and efficient global optimization for conceptual rainfall- runoff models. *Water Resources Research, 28*(4), 1015-1031.

Eckhardt, K., & Arnold, J. (2001). Automatic calibration of a distributed catchment model. *Journal of Hydrology, 251*(1), 103-109.

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASABE, 50*(4), 1211-1250.

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering, 4*(2), 135-143.

Hasan, Abu, Z., Nuramidah Hamidon , Norazazi Zakaria, Ghani, A. A., & Siang, a. L. C. (2009). "INCOPERATING GIS IN WATER RESOURCES MODELLING: Application of SWAT 2005 Model in Sungai Kurau, Perak and CCHE2D Model in Tasik Harapan USM, Penang"

Hülsmann, L., Geyer, T., Schweitzer, C., Priess, J., & Karthe, D. (2015). The effect of subarctic conditions on water resources: initial results and limitations of the SWAT model applied to the Kharaa River Basin in Northern Mongolia. *Environmental Earth Sciences, 73*(2), 581-592.

Ismail, W., & Najib, S. (2011). Sediment and nutrient balance of Bukit Merah Reservoir, Perak (Malaysia). *Lakes & Reservoirs: Research & Management, 16*(3), 179-184.

Kim, B. S., Kim, H. S., & Seoh, B. H. (2004). Streamflow simulation and skewness preservation based on the bootstrapped stochastic models. *Stochastic Environmental Research and Risk Assessment, 18*(6), 386-400.

Krishnan, N., Raj, C., Chaubey, I., & Sudheer, K. (2018). Parameter estimation of SWAT and quantification of consequent confidence bands of model simulations. *Environmental Earth Sciences, 77*(12), 470.

Kuczera, G., & Parent, E. (1998). Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. *Journal of Hydrology, 211*(1), 69-85.

Lane, L. J. (1983). *Chapter 19: Transmission Losses. p. 19-1, 19-21. In Soil Conservation Service.* U.S. Goernment Printing Office, Washington, D.C.

Lenhart, T., Eckhardt, K., Fohrer, N., & Frede, H.-G. (2002). Comparison of two different approaches of sensitivity analysis. *Physics and Chemistry of the Earth, Parts A/B/C, 27*(9), 645-654.

Lohani, A., Kumar, R., & Singh, R. (2012). Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. *Journal of Hydrology, 442*, 23-35.

Mahmoud, S. H., Adamowski, J., Alazba, A., & El-Gindy, A. (2016). Rainwater harvesting for the management of agricultural droughts in arid and semi-arid regions. *Paddy and Water Environment, 14*(1), 231-246.

McMillan, H., Jackson, B., Clark, M., Kavetski, D., & Woods, R. (2011). Rainfall uncertainty in hydrological modelling: An evaluation of multiplicative error models. *Journal of Hydrology, 400*(1), 83-94.

Nandakumar, N., & Mein, R. G. (1997). Uncertainty in rainfall—runoff model simulations and the implications for predicting the hydrologic effects of land-use change. *Journal of Hydrology, 192*(1), 211-232.

Narsimlu, B., Gosain, A. K., Chahar, B. R., Singh, S. K., & Srivastava, P. K. (2015). SWAT model calibration and uncertainty analysis for streamflow prediction in the Kunwari River Basin, India, using sequential uncertainty fitting. *Environmental Processes, 2*(1), 79-95.

Ning, J., Gao, Z., & Lu, Q. (2015). Runoff simulation using a modified SWAT model with spatially continuous HRUs. *Environmental Earth Sciences, 74*(7), 5895-5905.

Park, J.-Y., Yu, Y.-S., Hwang, S.-J., Kim, C., & Kim, S.-J. (2014). SWAT modeling of best management practices for Chungju dam watershed in South Korea under future climate change scenarios. *Paddy and Water Environment, 12*(1), 65-75.

Patel, D. P., & Srivastava, P. K. (2013). Flood hazards mitigation analysis using remote sensing and GIS: correspondence with town planning scheme. *Water Resources Management, 27*(7), 2353-2368.

Schuol, J., Abbaspour, K. C., Srinivasan, R., & Yang, H. (2008). Estimation of freshwater availability in the West African sub-continent using the SWAT hydrologic model. *Journal of hydrology, 352*(1), 30-49.

SCS. (1956). *Hydrology. National Engineering Handbook, Supplement A, Section 4. Soil Conservation Service* (Vol. US Department of Agriculture:Washington, DC; Chapter 10.).

Setegn, S. G., Srinivasan, R., & Dargahi, B. (2008). Hydrological modelling in the Lake Tana Basin, Ethiopia using SWAT model. *The Open Hydrology Journal, 2*(1).

Talebizadeh, M., Morid, S., Ayyoubzadeh, S. A., & Ghasemzadeh, M. (2010). Uncertainty analysis in sediment load modeling using ANN and SWAT model. *Water Resources Management*, *24*(9), 1747-1761.

Tangang, F. T., Juneng, L., & Ahmad, S. (2007). Trend and interannual variability of temperature in Malaysia: 1961–2002. *Theoretical and Applied Climatology*, *89*(3-4), 127-141.

Tolson, B. A., & Shoemaker, C. A. (2007). Cannonsville reservoir watershed SWAT2000 model development, calibration and validation. *Journal of Hydrology*, *337*(1), 68-86.

Unami, K., & Kawachi, T. (2005). Systematic assessment of flood mitigation in a tank irrigated paddy fields area. *Paddy and Water Environment*, *3*(4), 191-199. (Paddy and Water Environment)

USDA-SCS. (1986). Urban Hydrology for Small Watersheds, Technical Release No. 55 (TR-55). *US Department of Agriculture, US Government Printing Office, Washington, DC*.

Van Griensven, A., Meixner, T., Srinivasan, R., & Grunwald, S. (2008). Fit-for-purpose analysis of uncertainty using split-sampling evaluations. *Hydrological sciences journal*, *53*(5), 1090-1103.

Winchell, M., Srinivasan, R., Di Luzio, M., & Arnold, J. (2007). ArcSWAT interface for SWAT2005 User's guide. *Texas Agricultural Experiment Station and United States Department of Agriculture, Temple, TX*.

Wong, C., Venneker, R., Jamil, A., & Uhlenbrook, S. (2011). Development of a gridded daily hydrometeorological data set for Peninsular Malaysia. *Hydrological Processes*, *25*(7), 1009-1020.

Yadav, S. K., Singh, S. K., Gupta, M., & Srivastava, P. K. (2014). Morphometric analysis of Upper Tons basin from Northern Foreland of Peninsular India using CARTOSAT satellite and GIS. *Geocarto International*, *29*(8), 895-914.

Yang, J., Reichert, P., Abbaspour, K., Xia, J., & Yang, H. (2008). Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. *Journal of Hydrology*, *358*(1), 1-23.

Yeh, W. W. G. (1985). Reservoir management and operations models: A state- of- the- art review. *Water Resources Research*, *21*(12), 1797-1818.

Yesuf, H. M., Melesse, A. M., Zeleke, G., & Alamirew, T. (2016). Streamflow prediction uncertainty analysis and verification of SWAT model in a tropical watershed. *Environmental Earth Sciences*, *75*(9), 806.

Zhou, J., Liu, Y., Guo, H., & He, D. (2014). Combining the SWAT model with sequential uncertainty fitting algorithm for streamflow prediction and uncertainty analysis for the Lake Dianchi Basin, China. *Hydrological Processes*, *28*(3), 521-533.