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Most Sensitive Parameters of Soil and Water Assessment Tool (SWAT) Hydrological Model: A Review

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Abstract

Hydrological models are becoming more and more important instruments for hydrological base infrastructure planning, design, and management. However, there is uncertainty on using because of the varying nature. The key to establishing the uncertainty of a quantitative model is to analyze the sensitivity test of a hydrological model. The determination of the most sensitive parameters was the key and first step for model calibration and validation at the watershed scale. It is the process of identifying the model parameters that exert the greatest influence on model calibration or on model predictions. The SWAT is a watershed scale, continuous-time, semi-distributed hydrological model that predicts stream flow, sediments, nutrient loading, and pesticide transport by incorporating meteorological data, soil properties, land cover/use, and management methods. The model requires calibration and validation. Before the calibration and validation works are started the sensitive parameters of the model has to be determined. The most sensitive SWAT hydrological model parameters are base flow alpha factor (ALPHA_BF), soil evaporation compensation factor (ESCO), available water capacity (SOL_AWC), groundwater delay (GW_DELAY), saturated hydraulic conductivity (SOL_K), initial curve number (II) value (CN2), shallow aquifer flow threshold (GWQMN), effective hydraulic conductivity in main channel alluvium (CH_K2), manning's n value for the main channel (CH_N2) and surface runoff lag time (SURLAG). The sensitivity depends not only on the physiographic and meteorological characteristics of the study area, but also on the sensitivity analysis methodologies applied.

Keywords: Calibration and Validation; Hydrological Models; Sensitive Parameters; SWAT

Introduction

Hydrological models are useful tools that have been used in recent years to provide a visual representation of hydrological processes as well as accurate flow simulations, especially when evaluating the effects of land-use change and climate variability on hydrological cycles and water balance components [1]. They are helpful tools for managers, water resource planners, and academicians in understanding complex hydrological and water quality processes at the watershed scale, as well as decision support tools. Simulated discharges aid in anticipating the effects of various land uses and soil management methods on water resources, sediment yield, and water quality [2,3]. They are also used to forecast floods and droughts and for irrigation management. To accomplish these goals, the model must show that it can accurately simulate hydrological processes and forecast hydrological responses in the studied watershed, such as floods, droughts, soil erosion, and water quality [4]. The Soil and Water Assessment Tool (SWAT) continues to receive a lot of attention among the numerous hydrological models [4,5].

The SWAT is a watershed-scale, continuous-time, and semi-distributed hydrological model that incorporates meteorological elements, soil characteristics, land cover/use, and management practices to predict mainly stream flow, sediments, nutrient loading, and pesticide transport [6]. It enables the simulation of spatial details by dividing the whole watershed into a series of sub-watersheds. Each sub-watershed then comprises hydrologic response units (HRUs) that represent homogenous soil properties, land cover, and slopes. Surface runoff, soil water, nutrient cycles, sediment, and crop yields are calculated within each HRU (i.e., the smallest element), and they are subsequently lumped into the sub-catchment using the weighted mean method and finally routed into river systems. Four types of water storage are assumed for simulation: surface runoff, soil water, and shallow and deep aquifers.

Data collection, database generation, and model simulation are all preliminary stages in the development of the SWAT model. The next step is to examine the model's sensitivity test before performing calibration and validation. The key to establishing the uncertainty of a quantitative model is to analyze the sensitivity test of a hydrological model [7]. If a little change in the input parameter causes the output to alter dramatically, the output is particularly sensitive to the input parameter. Individual input contributions to the uncertainty in the model output are determined through sensitivity analysis. It will be determined based on the hypothesis that the input parameters are relevant, that the parameters interact with one another, that the parameters are constant, or that the input parameters are insignificant to the output. Focusing on the sensitive factors can provide insights and forecast values, reducing model uncertainty. As a result, it tries to streamline complicated system models in terms of time, effort, and costs associated with their use.

The determination of the most sensitive parameters was the key and first step for model calibration and validation at the watershed scale. It is the process of identifying the model parameters that exert the greatest influence on model calibration or on model predictions. Generally, the sensitivity of the parameters used in a SWAT model is grouped into three categories: sensitive, less sensitive, and insensitive [8,9]. Sensitive parameters are the parameters that have a significant effect on the output. Less sensitive parameters are the parameters that have a little effect on the output in the presence of several changes in values, whereas insensitive parameters are the parameters that do not affect the output. These sensitive parameters will be selected based on the calculated value of t-stat and P-value. The larger the absolute value of t-stat and the smaller the p-value, the more sensitive the parameter is considered [10,11].

Most academicians and modelers face a challenge while simulating the SWAT model, since determining the sensitive parameters before calibrating and validating the model is essential. However, they spent a significant amount of time without considering the most sensitive parameters, resulting in a biased decision. Therefore, the objective of this paper was to review the most sensitive parameters of the SWAT model at a watershed level.

Hydrological Processes

Water can exist in three states: gaseous, liquid, and solid. Solar and planetary forces mostly circulate it on the planet Earth. Various hydrologic phenomena occur in nature as a result of this circulation. The hydrologic cycle is the ongoing chaining of hydrologic events. As a result, evaporation transports water from the ocean to the atmosphere as vapor, precipitation from the atmosphere to the land, and runoff from the land to the ocean. The hydrologic cycle, in general, is infinite since it has neither beginning nor end. As a result, hydrologic phenomena are exceedingly complicated, making them difficult to quantify and comprehend in depth. In the absence of an expert, they can be simplified using the system notion, which is a collection of interconnected pieces that constitute a whole [12,13].

The hydrological cycle is assumed to be a closed system in hydrology, meaning there are no gains or losses of water from the cycle. Unfortunately, the hydrologist will frequently encounter an open system that can only be characterized using a mass balance or water budget equation, in which the difference between input [I] and output (O) is proportional to the change in storage (DS) over time.

Because of these significant complexities, it is impossible to utilize exact physical principles to explain all of the physical processes occurring within the watershed. Instead, using the physical system approach, the work is focused on creating a model that represents the most significant processes and their interactions within the overall system. A conceptual understanding of the physical system will be important in determining the main processes and developing a simple but usable model. This form of study is known as conceptual modeling [12].

Overview of hydrological models

Mathematical models have become increasingly feasible for operational hydrology and water-resource system planning and management as a result of real-time forecasting, control, prediction, planning, and design [14]. They're the instruments that decision-makers can utilize to forecast and predict water supply and quality [15]. Some of these models may also forecast the effects of natural and anthropogenic changes on water resources, as well as quantify the resources' spatial and temporal availability. The difficulties lie in selecting and applying these models to a specific basin and management strategy.

Models are becoming more and more important instruments for hydrological base infrastructure planning, design, and management. It's widely utilized and has a significant impact on water management, policy development, and research [16]. Models are defined by the reason for application, which might range from policy to scientific research. A model is a system methodology technique that aids in the definition and evaluation of several options that represent various possible compromises among conflict parties, values, and management goals [17].

Several models have been developed to simulate river basin water development and management regimes. Each of these models is built on a node-link network representation of the simulated water resource system. All include menu-driven graphics-based interfaces to make user interaction easier (18). These models are suitable for use in shared vision activities that include stakeholder participation in model development and simulations. One of the most often used hydrological models today is the soil and water assessment tool (SWAT) [19-23].

Description of SWAT model

SWAT model is one of the most recent models developed in the United States Department of Agriculture Agricultural Research Service during the early 1970s. It is a physically based watershed scale continuous time-scale model, which operates on a daily time step. It delineates a watershed, and sub-divides that watershed into sub-basins. In each sub-basin, the model creates several HRUs based on specific land cover, soil, and topographic conditions [24].

The SWAT is a watershed-scale, continuous-time, semi-distributed hydrological model that predicts stream flow, sediments, nutrient loading, and pesticide transport by incorporating meteorological data, soil properties, land cover/use, and management methods [24]. By separating the entire watershed into a succession of sub-watersheds, it allows for the modelling of geographical features. Hydrologic response units (HRUs) represent homogeneous soil qualities, land cover, and slopes in each sub-watershed. Each HRU (i.e, the smallest element) calculates surface runoff, soil water, nutrient cycles, sediment, and agricultural yields, which are then lumped into the sub-catchment using the weighted mean approach and then routed into river systems. Mostly for simulation, four forms of water storage are assumed: surface runoff, soil water, shallow and deep aquifers [25,26]. The model implies that shallow groundwater flows as base flow into the river channel or evaporates back into the soil, whereas deep aquifer flows exit the watershed system.

The model works with spatial and temporal data [26-28]. Spatial data include elevation, soil type, slope and land use/cover. For delineation, the watershed Digital Elevation Model (DEM) grid, digitized stream network files have to be loaded using the watershed delineation tool. Land use and land cover is also one of the most important spatial input data in SWAT Model. It will be reclassified according to requirement of the SWAT model. The SWAT model also requires soil data as a spatial input. For different layers of each soil type, the SWAT model requires distinct soil textural and physicochemical parameters such as soil texture, accessible water content, hydraulic conductivity, bulk density, and organic carbon content [29]. Meteorological datasets and stream flow data constitute the model's temporal input datasets. The SWAT model requires stream flows as supplementary temporal input data for calibration and validation. Arc SWAT requires stream flow data as an input for calibration and validation [30,31].

Calibration and validation procedures reduce uncertainty and boost user trust in the model's forecasting abilities. Using a larger data set for model calibration increases the model's simulation and prediction confidence [32]. The Nash-Sutcliffe coefficient of efficiency (NSE) [33] and coefficient of determination (R2) are commonly used to calibrate and validate the SWAT model.

Model calibration entails changing parameter values until the model-predicted output closely matches the observed output, as judged by objective error functions [24]. A statistical test that reduces relative and average error or optimizes the NSE is used as the objective function for model calibration [34-36]. The calibrated parameters must, however, be within realistic ranges for the watershed in question [24]. Validation processes involve testing the calibrated model's ability to predict specific outputs using various data sets. Validation determines if the model was calibrated exclusively for a specific dataset or if it accurately represents the watershed's hydrological behavior [37]. If the validation dataset's objective function is not met, the calibration and/or model assumptions should be reconsidered.

Sensitivity analysis of the SWAT model

The sensitivity analysis method combines Latin-Hypercube and One-factor-At-a-Time (LH OAT) sampling to provide a global sensitivity analysis for a large number of parameters with a small number of models runs. SWAT comprises 26 parameters for stream flow, 6 for sediment, and 9 for nutrients.

Sensitivity analysis is a crucial aspect of model creation, and it entails a thorough assessment of input parameters to improve model validation and provide direction for future research. According to [33], seven SWAT sensitive parameters were identified under various temporal simulations, including the flow recession constant or proportional to the riverbanks (Alpha BNK), the initial SCS runoff curve number for moisture condition II (CN2), effective hydraulic conductivity in main channel alluvium (CH K2), Manning's "n" value for the main channel (CH N2), and groundwater delay time (GW Del). Due to similarity of soil properties, there are no differences observed on the sensitive parameters for different spatial data resolutions.

It is possible to evaluate model-sensitive parameters by a multiple regression system calculation. The sensitivity can be determined using the t-test, and the significance of parameter sensitivity is determined by the value of p. The closer the value of p is to zero, the greater the significance and sensitivity. A model parameter is identified as a sensitive one when the value of p is less than or equal to 0.05. Following the same methodology, a study conducted by [38] reveals that, at the significance level of 0.05, the sensitive calibration parameters found using three-year discharge data are ALPHA_BNK, GW_DELAY, and SURLAG; whereas the sensitive parameters of calibration using one year of data are ALPHA_BNK, CN2, ESCO, GW_DELAY and SURLAG; the sensitivity parameters of calibration using only one year of data are ALPHA_BF, ALPHA_BNK, and SURLAG; sensitivity parameters of calibration using another only one year data are ALPHA_BNK, ESCO, GW_REVAP and SURLA. The study reveals that the sensitive parameters derived from the four model calibrations are different, which indicates the information content in the four calibration datasets is different.

The importance of SWAT sensitive parameters varies depending on land use, topography, and soil types [39]. According to the study conducted by [15], 15 hydrologic parameters and 13 sediment and nutrient parameters in the SWAT model were sensitive. The sensitive parameters were namely, 15 hydrologic parameters such as (ALPHA_BF (Base flow alpha factor), CANMX (Maximum canopy storage), CH_K2 (Effective hydraulic conductivity in main channel alluvium), CH_N2 (Manning's n value for the main channel), CN2 (SCS runoff curve number), EPCO (Plant water uptake compensation factor), ESCO (Soil evaporation compensation factor), GW_DELAY (Groundwater delay time), GW_REVAP (Groundwater "revap" coefficient), GWQMN (Threshold depth of water in the shallow aquifer required for return flow to occur), SLOPE, SOL_AWC (soil available water content), SOL_K (Soil saturated hydraulic conductivity), SOL_Z (Depth from soil surface to bottom of layer), SURLAG (Surface runoff lag time) and 13 sediment and nutrient parameters (CH_COV (Channel cover factor), CH_EROD (Channel erodibility factor), NPERCO (Nitrate percolation coefficient), PHOSKD (Phosphorus soil partitioning coefficient), PPERCO (Phosphorus percolation coefficient), RCHRG_DP (deep aquifer percolation fraction), SOL_LABP (initial soluble P concentration in soil layer), SOL_NO3 (Initial NO3 concentration in the soil layer), SOL_ORGN (Initial organic N concentration in the soil layer), SOL_ORGP (Initial organic P concentration in soil layer), SPCON (Linear parameter for calculating the maximum amount of sediment that can be reentered during channel sediment transport routing), SPEXP (Exponent parameter for calculating sediment re-entered in channel sediment routing), USLE_P (USLE equation support practice factor). The study revealed that the SWAT output variables were most sensitive to the hydrologic parameters. It also showed that water quality variables were potentially capable of contributing to the identification of water quantity parameters within the SWAT model, and a single parameter was correlated to multiple variables.

[40] studied the calibration and validation of the SWAT model, as well as the estimation of water balance components in the Shaya mountainous watershed in Ethiopia and found the following sensitive parameters among twenty-seven flow parameters: The groundwater parameters were found to be more sensitive to stream flow than the other sensitive flow parameters [40]. The most effective hydrologic parameters for the simulation of stream flow were found to be Soil evaporation compensation factor (ESCO), Soil depth (SOL Z), Threshold water depth in the shallow aquifer for "revap" (REVAP-min), Maximum potential leaf area index (BLAI), Available water capacity (SOL AWC), Maximum canopy storage (CANMX), Groundwater Delay (GW DELAY), Saturated hydraulic conductivity (SOL K), Surface runoff lag time (SURLAG), Deep aquifer percolation fraction (RCHRG_DP), Initial curve number (II) value (CN2), Base flow alpha factor (ALPHA_BF), and Threshold water depth in the shallow aquifer for flow (GWQMN).

According to the study conducted by [41], for the sensitivity analysis and evaluation of forest biomass production potential using SWAT model on local sensitivity analysis of seven crop parameters namely radiation use efficiency (kg/ha)/(MJ/m2) (BIOE), potential maximum leaf area index for the plant (BLAI), fraction of growing season at which senescence becomes the dominant growth process (DLAI), fraction of the maximum plant leaf area index corresponding to the 1st point on the optimal leaf area development curve (LAIMX1), fraction of growing season corresponding to the 1st point on the optimal leaf area development curve (FRGRW1), plants potential maximum canopy height (m) (CHTMX), and maximum rooting depth for plant (mm) (RDMX) to predict forest biomass production and determined three parameters: DLAI , BIOE and BLAI as sensitive to predict forest biomass production. DLAI and BIOE are moderately sensitive and BLAI shows low sensitivity [41]. The sensitivity analysis conducted may provide baseline information about the sensitivity of seven crop parameters of SWAT to influence forest biomass production.

During model calibration for the Laou watershed, parameters linked to topographical variation and land use were more sensitive; also, parameters related to soil and groundwater were more sensitive for modelling this basin [26]. The analysis of these different physical and geomorphological (lithological) parameters allows a better understanding of the causes of variations in the hydrological regimes of the studied watershed area and, consequently, their contribution to the genesis of floods. Their interaction determines the variability of hydrological phenomena in time and space. Accordingly, from the selected 28 sensitive parameters, six parameters were identified as the most important sensitive parameters. The sensitive parameters were the initial SCS runoff curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), available water capacity of the soil layer (SOL_AWC), base flow alpha factor (ALPHA_BF), manning's n value for the main channel (CH_N2), Effective hydraulic conductivity in main channel alluvium (CH_K2) [26].

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Summary

Even though models are simplified versions of reality, they all go through some form of conceptualization, and their outcomes are only as realistic as the model assumptions and algorithms, the quality and quantity of inputs, and parameter estimations. Before deploying models for their intended purposes, it is critical to create a system that increases the quality of model estimates based on observable information available to the modeler. Identifying values of model parameters so that model simulations closely reflect actual behavior is a popular technique to perform this useful task. However, during selecting sensitive parameters, one of the most significant tasks is to reduce the number of parameters that should be carried for a specific task.

Although SWAT is a physically based model, some phenomena are represented by empirical functions, such as, runoff, for that reason CN is important during the modelling. ESCO soil evaporation compensation factor, this parameter enables to vary the quantity of water that can be extracted from the ground to meet the evaporative demand; the CH_K2 parameter influences the exchanges between the river and the groundwater and therefore makes the watercourse less impermeable.

According to various studies, the most sensitive SWAT hydrological model parameters are base flow alpha factor (ALPHA_BF), soil evaporation compensation factor (ESCO), available water capacity (SOL_AWC), groundwater delay (GW_DELAY), saturated hydraulic conductivity (SOL_K), initial curve number (II) value (CN2), shallow aquifer flow threshold (GWQMN), effective hydraulic conductivity in main channel alluvium (CH_K2), manning's n value for the main channel (CH_N2) and surface runoff lag time (SURLAG).

The sensitivity of the SWAT model's hydrologic parameters depends not only on the physiographic and meteorological characteristics of the study area, but also on the sensitivity analysis methodologies applied. Variations in the number of iterations, the location of the fluviometric station, and the duration of historical records can also alter sensitive parameters.

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Conflict of Interest

No Conflict of interest.

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