Journal of Spatial Hydrology

Volume 14 | Number 2 Article 3

2018

# Hydrological Modeling in the Ong River Basin, India using SWAT Model

Journal of Spatial Hydrology Vol.14, No.2 Fall 2018

# Hydrological Modeling in the Ong River Basin, India using SWAT Model

**S. C. Ghadei[1], P.K. Singh[2], S.K. Mishra[1]**
[1]Dept. of Water Resources Development & Management, IIT Roorkee, Uttarakhand
[2]National Institute of Hydrology, Roorkee, Uttarakhand

**Abstract**

The Ong river basin, a tributary of the Mahanadi River (a major river basin in eastern India) needs an effective management of water resources due to flood severity for sustainable agricultural production and flood protection. The Soil and Water Assessment Tool (SWAT) was used in this study for setting up a watershed model for discharge simulation in the basin. SWAT-CUP (SWAT-Calibration and Uncertainty Program) that enables calibration, sensitivity and uncertainty analysis with the Sequential Uncertainty Fitting (SUFI-2) technique was used in the study. The SWAT model was calibrated from 1981–1990 (warm up period: 1979–1981); and validated from1991-2000. The goodness of fit of the model calibration and uncertainty was assessed using two indices, i.e., p-factor and r-factor. These measures together indicate the strength of the calibration-uncertainty analysis of SWAT model. During calibration, the p and r values were obtained as 0.75 and 0.82, respectively, while during validation, the p and r were found as 0.72 and 0.65, respectively. As per the results of this study, the SWAT model can be efficiently used in the Ong basin by water resources' managers for managing droughts and floods, agricultural water management, and planning for soil and water conservation structures.

**Keywords:** P-factor, R-factor, Runoff, SWAT, SWAT-CUP, SUFI2

## Introduction

Water resources management problems involve complex processes from surface and subsurface level to their interface regimes (Sophocleous, 2002; Srivastava et al. 2013b). Hydro-geologic characteristics within a watershed system are heterogeneous in nature with respect to time and space, thus making water resources management very challenging. In recent years several semi-distributed models of watershed models have been successfully employed to address a wide spectrum of environmental and water resources problems. Hydrological watershed models are very useful and effective tools in water resources management (Patel and Srivastava, 2013 & 2014), particularly in assessing impacts and influence of land use/land cover and climate change on water resources (Narsimlu et al., 2013; Singh and Saraswat, 2016; Srivastava et al., 2008 & 2013a).

Among semi-distributed hydrological models, the Soil and Water Assessment Tool (SWAT) model was originally developed for prediction of discharge from ungauged basins (Arnold et al., 1998). The model has been successfully used to simulate flows, sediment and nutrient loadings from watersheds (Rosenthal and Hoffman, 1999). SWAT model has been used extensively in many countries worldwide for discharge prediction as well as for soil and water conservation (Patel and Srivastava, 2013; Spruill et al., 2000; Zhang et al., 2010). The model has also been successfully applied for water quantity and quality assessments for a wide range of scales and environmental issues (Faramazi et al., 2009; Schuol et al., 2008; Singh, 2012). Several other studies such as hydrological impact of forest fires (Batelis and Nalbantis, 2014); non-point source pollution (Wang et al., 2011; Hong et al., 2012; Singh and Leh, 2018); impact of climate changes and human activities on water resources (Guo et al., 2008; Li et al., 2009; Huang and Zhang, 2004) have been conducted using the model. Zang et al. (2012) simulated spatial and temporal patterns of blue and green water flows by SWAT model for the Heihe river basin. Schuol et al. (2008b) and Zang et al. (2012) used SWAT model for evaluating blue and green water availability in Africa and Heihe River Basin (north east China) respectively. Fiseha et al. (2014) applied SWAT for the study of hydrological responses to climate change in the Upper Tiber River basin using bias corrected daily Regional Climate Model (RCM) outputs. Srinivasan et al. (2010) evaluated the performance of a SWAT model for hydrologic budget and crop yield simulations in the Upper Mississippi River Basin without calibration (ungauged basin). Gosain et al. (2006) applied SWAT model for hydrological modeling of 12 major river basins in India, including the Ganga, the Cavery, the Krishna, the Godavari and the Mahanadi river basins. Spruill et al. (2000) calibrated and validated a SWAT model for a small experimental watershed in Kentucky, USA and found that the monthly flows were simulated more accurately. Arnold and Allen (1996) successfully used SWAT model to estimate surface runoff, groundwater flow, groundwater recharge parameters in three Illinois watersheds. Rodrigues et al. (2014) used SWAT to develop a framework to quantify blue and green water in a catchment located at Sao Paulo, Brazil. Shinde et al. (2017) used SWAT to study potential hydrological effects of abandoned opencast coal mines of Olidih Watershed in Jharia Coalfield, India. More recently, SWAT was also used to evaluate the impact of conservation practices on flow and water quality (Leh et al., 2018; Singh et al., 2018)

Evaluation of parameter uncertainties of distributed models has also gained popularity in hydrological sciences (Beck, 1987; Beven and Binley, 1992; Yatheendradas et al., 2008), biosciences (Blower and Dowlatabadi, 1994), atmospheric sciences (Derwent and Hov, 1988) and structural sciences (Adelman and Haftka, 1986). Sensitivity and Uncertainty analyses (SA and UA) are essential processes to reduce uncertainties imposed by variations of model parameters and structure (Gupta et al., 2006; Srivastava et al., 2013c; Wagener and Gupta, 2005). Calibration and uncertainty analysis techniques for watershed models include: MCMC (Markov Chain Monte Carlo) method (Vrugt et al., 2008), GLUE (Generalized Likelihood Uncertainty Estimation) (Beven and Binley, 1992), ParaSol (Parameter Solution) (Yang et al., 2008), and SUFI-2 (Sequential Uncertainty Fitting) (Abbaspour et al., 2004). These techniques (GLUE, Parasol, SUFI-2 and MCMC) have been linked to SWAT model through a SWAT-CUP algorithm (Abbaspour et al., 2007) and enabling SA and UA of model parameters as well as structural uncertainty (Rostamian et al., 2008). Studies on model calibration and Uncertainty Analysis have emphasized that SWAT model is an effective tool in managing water resources (Tang et al., 2012). Abbaspour et al. (2004) and Yang et al. (2008) applied the SUFI-2 technique for evaluation of SWAT model. The SUFI-2 technique needs a minimum number of model simulations to attain a high-quality calibration and uncertainty results (Yang et al., 2008).

With this background, the main objectives of this study were calibration, uncertainty analysis, and validation of a SWAT model developed to assess its capability in predicting runoff in the Ong basin. Model calibration and validation were conducted through sensitivity analysis and uncertainty analysis using the SUFI-2 algorithm in SWAT CUP (Blasone et al., 2008; Srivastava et al., 2013d; Wagener and Wheater, 2006; Zheng and Keller, 2007).

## Methods

*Description of Study Area:*

The Ong river basin is a sub-basin of the Mahanadi river basin of the Odisha State in Eastern India and it is located between latitudes 20° 41′ 18″ N to 21° 29′ 38″ N and longitudes 82° 33′ 35″ E to 83° 50′ 46″ E (Figure **1**). It is an agricultural dominated basin with a drainage area of 5121 $km^2$. The altitude varies from 533 m in the western part to 115m in the eastern part. Major crops in this area are rice, sugarcane, groundnut, potatoes, black gram, bengal gram, mustard, sunflower and vegetables. Most of the annual precipitation falls during the monsoon period, i.e., from July to October ranging from 750 to 1614 mm and the average being 1614 mm. Maximum temperature in April and May ranges from 40 to 49 °C, whereas the minimum temperature occurs during the months of December and January ranging from 9 to 14 °C.

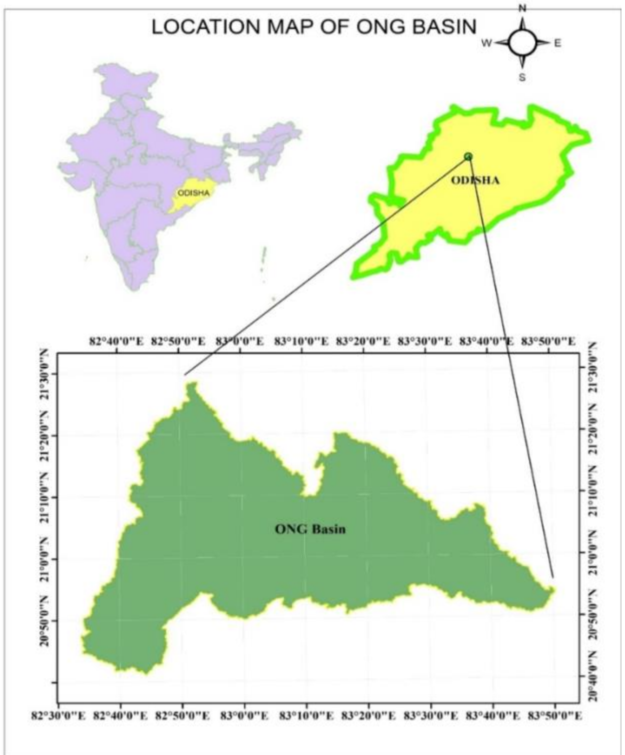


Figure 1.Location map of Ong river basin

*The SWAT model:*

The SWAT model (Arnold et al., 1998) is a physically based, semi-distributed catchment (river basin) model developed to quantify impacts of land management practices on surface waters by simulating evapotranspiration, plant growth, infiltration, percolation, runoff and nutrient loads, and erosion (Neitsch et al., 2011). The model has been tested (e.g. for agricultural water management purposes) and discussed extensively in literature. This model is capable of continuous simulation over a long period of time. Catchment processes in SWAT are modeled in two phases – the land phase, covering the loadings of water, sediment, nutrients, and pesticides from all sub-basins to a main channel, and the water routing phase, covering processes in the main channel to the catchment outlet (Neitsch et al., 2011). In SWAT, a "catchment" is further divided into sub-basins and Hydrologic Response Units (HRUs), of which the latter are unique combinations of land use, soil, and slope. We used SWAT 2012 (Revision 622) for our modeling activity. There are two methods in SWAT for estimating surface runoff (i) Modified SCS curve number (CN) and (ii) Green-Ampt infiltration method. Here we used SCS-CN method for estimating surface runoff volume. SWAT model has three methods for estimating potential evapotranspiration: Priestley-Taylor, Penman-Monteith (PM) and Hargreaves methods. We used the PM method for estimating evapotranspiration. Lateral flow was simulated by kinematic storage model and return flow is estimated by creating a shallow aquifer (Arnold et al., 1998). Channel flood routing was computed by using the Muskingum method and transmission losses, evaporation, return flow etc., are adjusted for estimation of outflow from a channel (Baymani-Nezhad and Han, 2013).

In the model, water balance Eq. (1), which governs the hydrological balance is expressed as (Neitsch et al., 2005):

$$SW_t = SW_0 + \sum_{i=1}^{i=t} \left( R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw} \right) \tag{1}$$

where: $SW_t$ is the final soil water content (mm); $SW_0$ is the initial soil water content on day i (mm); $R_{day}$ 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 (ET) on day i (mm); $W_{seep}$ is the amount of water entering the vadose zone from the soil profile on day i (mm); $Q_{gw}$ is the amount of return flow on day i (mm).

*Calibration and uncertainty analysis tool SUFI-2 Procedure:*

The SUFI-2 method embedded in SWAT-CUP interface (Abbaspour et al., 2007) was used for model calibration and uncertainty analysis. In this method all uncertainties (parameter, conceptual model, input, etc.) are mapped onto the parameter ranges, which are calibrated to bracket most of the measured data in the 95% prediction uncertainty (95PPU) (Abbaspour et al., 2007). Latin hypercube sampling method was employed for 95PPU and for obtaining the final cumulative distribution of the model outputs. The overall uncertainty analysis in the output was calculated by the 95% prediction uncertainty (95PPU). Two different indices, i.e., p-factor and r-factor were used for the comparison between observed and simulated discharge. The p-factor is the percentage of data bracketed by the 95PPU band. The maximum value for the p-factor is 100 %, and ideally, we bracket all measured data, except the outliers, in the 95PPU band. The r-factor is the average width of the band divided by the standard deviation of the corresponding measured variable (Abbaspour, 2007; Faramarzi et al., 2009). The r-factors were calculated as the ratio between the average thickness of the 95PPU band and the standard deviation of the measured data. It represents the width of the uncertainty interval and should be as small as possible.

The range of p-factor varies from 0 to 1, with values close to 1 indicating a very high model performance and efficiency, while r-factor is the average width of the 95PPU band divided by the standard deviation of the measured variable and varies in the range 0–infinity (Abbaspour et al., 2007; Yang et al., 2008). The p- and r-factors are closely related to each other, which indicates that a larger p-factor can be achieved only at the expense of a higher r-factor. After balancing these two factors, and at an acceptable value of the r and p-factors, a calibrated parameter ranges can be generated. The r-factor is given by Eq. (2) (Yang et al., 2008) as:

$$r - factor = \frac{\frac{1}{n}\sum_{ti=1}^{n}(y^{M}_{ti,97.5\%} - y^{M}_{ti,2.5\%})}{\sigma_{obs}} \qquad (2)$$

where: $y_{Mti;97:5\%}$ and $y_{Mti;2:5\%}$ are the upper and lower boundaries of the 95UB; and $\sigma_{obs}$ is the standard deviation of the observed data.

*SWAT Model Setup:*

The SWAT model mainly requires five types of data: a digital elevation model (DEM) of the study area, land use data, soil data, climate data, and other crop management data. DEM, land use, soil, weather and hydrology databases were collected from different sources/agencies and are given in Table 1.

*Digital Elevation Model (DEM):*

The DEM was used in delineating boundaries of the watershed and defining topographic parameters to simulate flow behavior and flow patterns. Input DEM data resolution impacts the watershed that is being delineated, number of subwatersheds created and number of HRUs created (Singh and Kumar, 2017 and Chaubey et al., 2005). Further, it also plays an important role in fast and slow runoff processes (Patel et al., 2013; Wagener and Wheater, 2006; Yadav et al., 2013). In this study, a 30 m×30 m ASTER digital layer (DEM) was obtained from the United States Geological Survey (USGS) global data repository. Table 2 show a brief description of percentage of area falling under different land slopes categories

*Land Use/Land Cover (LULC):*

The LULC map of the Ong river basin was prepared with Linear Imaging Self-Scanning Sensor-III (LISS-III) image by using ERDAS imagine software. The LULC map is shown in Figure **2**. The Ong river basin may be classified according to four major land use classes (Table 2) as per SWAT nomenclature: URHD (Residential-High Density) (1.25%), AGRL (Agricultural Land-Generic) (81.24%), FRST (Forest-Mixed) (14.36), PAST (Pasture) (1.05), and WATR (Water) (2.09%).

*Soil map:*

The Harmonized World Soil Database (HWSD) with 1 km resolution was used as listed in Table 1 and shown in Figure **3** was used to estimate major soil types and texture within the basin. The major soil groups are clayey loam followed by sandy loam and clay soils. The surface texture varies from sandy loam to loam, clay loam and even to clay. The alleviation of finer particles ensures fine texture of the middle horizons.

Table 1. Spatial data used for SWAT modeling in the Ong river basin

| SI. No | Type of data | Source |
|---|---|---|
| 1 | Satellite image | www.earthexplorer.usgs.gov |
| 2 | Landuse Map | developed in ERDAS IMAGINE |
| 3 | DEM | https://gdex.cr.usgs.gov/gdex |
| 4 | Soil data | http://webarchive.iiasa.ac.at/Research/LUC/External-Worldsoil- database/HTML |
| 6 | Precipitation | http://globalweather.tamu.edu/ |
| 7 | RH | http://globalweather.tamu.edu/ |
| 8 | Solar Radiation | http://globalweather.tamu.edu/ |
| 9 | Temperature | http://globalweather.tamu.edu/ |

| | | |
|---|---|---|
| 10 | Wind speed | http://globalweather.tamu.edu/ |
| 11 | Observed discharge | http://www.india-wris.nrsc.gov.in |

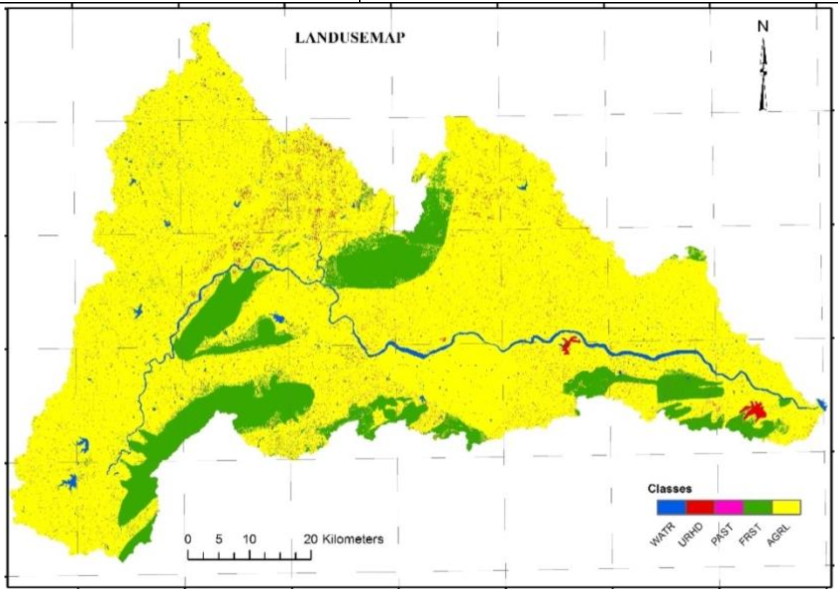


Figure 2. Land Use map of Ong river basin

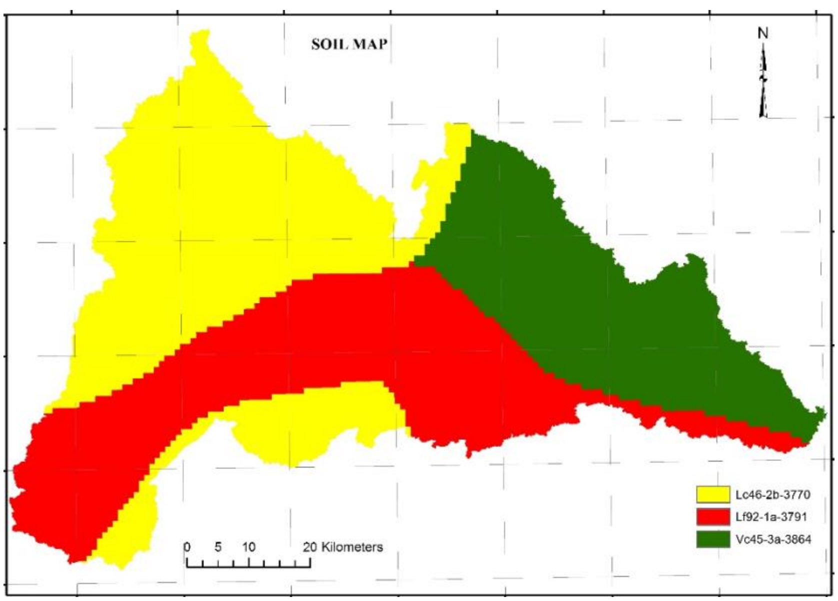


Figure 3. Soil map of Ong river basin

*SWAT Model Development and HRU Delineation:*

The basic input data for the SWAT model was prepared using an ArcGIS environment (ArcSWAT version 10.2) and following four basic steps: 1. Basin area/watershed and subbasin delineation, stream network and outlet definition, creation of hydrologic response units with respect to land slope, land use, soil types and then overlaying weather data (precipitation, relative humidity, temperature, wind flow, solar radiation). The DEM was used to delineate the watershed and generate 14 sub-watersheds for the entire basin area (Figure **4**). The subwatersheds were sub-divided to form 603 HRUs based on land use, slope and soils in the study area with a threshold area of 300 ha.

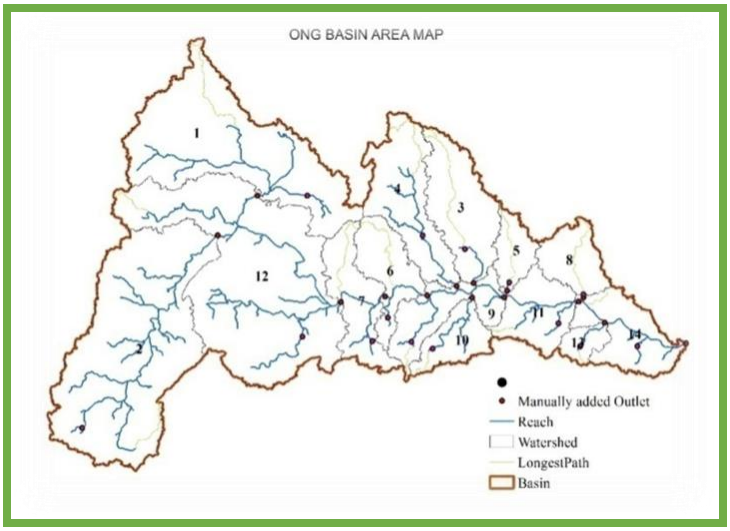


Figure 4. Sub-basin map of Ong river basin

Table 2. Details of watershed LANDUSE/SOIL/SLOPE distribution map for the Ong river basin

| Item | Area (ha) | | % of area | Remarks |
|---|---|---|---|---|
| **LANDUSE:** | | | | |
| URHD | 6412.23 | 15844.93 | 1.251 | Residential-High Density |
| AGRL | 416070.30 | 1028130.51 | 81.24 | Agricultural Land-Generic |
| FRST | 73527.26 | 181689.54 | 14.364 | Forest-Mixed |
| PAST | 5390.47 | 13320.12 | 1.051 | Pasture |
| WATR | 10727.75 | 26508.82 | 2.094 | Water |
| **Total** | **512128.01** | **1265493.92** | **100** | |
| **SOIL:** | | | | |
| Lc46-2b-3770 | 205429.03 | 507625.41 | 40.11 | Clay_loam |
| Lf92-1a-3791 | 176942.91 | 437234.77 | 34.55 | Sandy loam |

| | | | | |
|---|---|---|---|---|
| Vc45-3a-3864 | 129756.07 | 320633.75 | 25.34 | Clay |
| **Total** | **512128.01** | **1265493.92** | **100** | |
| **SLOPE:** | | | | |
| 0-0 | 570.85 | 1410.59 | 0.11 | |
| 0-5 | 102346.71 | 252903.85 | 19.98 | |
| 5-10 | 178350.27 | 440712.43 | 34.83 | |
| 10-15 | 115243.29 | 284771.94 | 22.5 | |
| >15 | 115616.88 | 285695.094 | 22.58 | |
| **Total** | **512128.01** | **1265493.92** | **100** | |

In this study, as suggested by Neitsch et al. (2005), while defining HRUs, the minor land use/land cover, slope and soil types were ignored by setting a threshold of 10 %, to avoid unnecessary large number of HRUs which might cause computational issues. Figure **5** shows the SWAT framework for runoff simulation.

*SWAT Model Calibration and Validation:*

In order to parameterize a model, calibration is done by changing selected parameters and comparing simulated outputs to their measured counter parts. Calibration is followed by validation to demonstrate a model's capability to perform and make sufficiently accurate site-specific hydrologic, sediment or nutrient predictions (Arnold et al., 2012).

Model calibration and validation can be a challenging and to a certain degree subjective step in a complex hydrological model. The SWAT model calibration and uncertainty analysis was performed using the SUFI-2 (Sequential Uncertainty FItting Ver. 2) algorithm within SWAT-CUP (Figure **5**). The calibrated parameters were used for validation of  results for Ong river basin. A monthly calibration and validation was done using discharge data at Salebhata gauging site. The discharge data at Salebhata gauging site were obtained from India-WRIS website (http://india-wris.nrsc.gov.in/wris.html) for the period 1979-2000 and were increased in area-ratio to obtain discharge at the outlet of the Ong sub-basin.

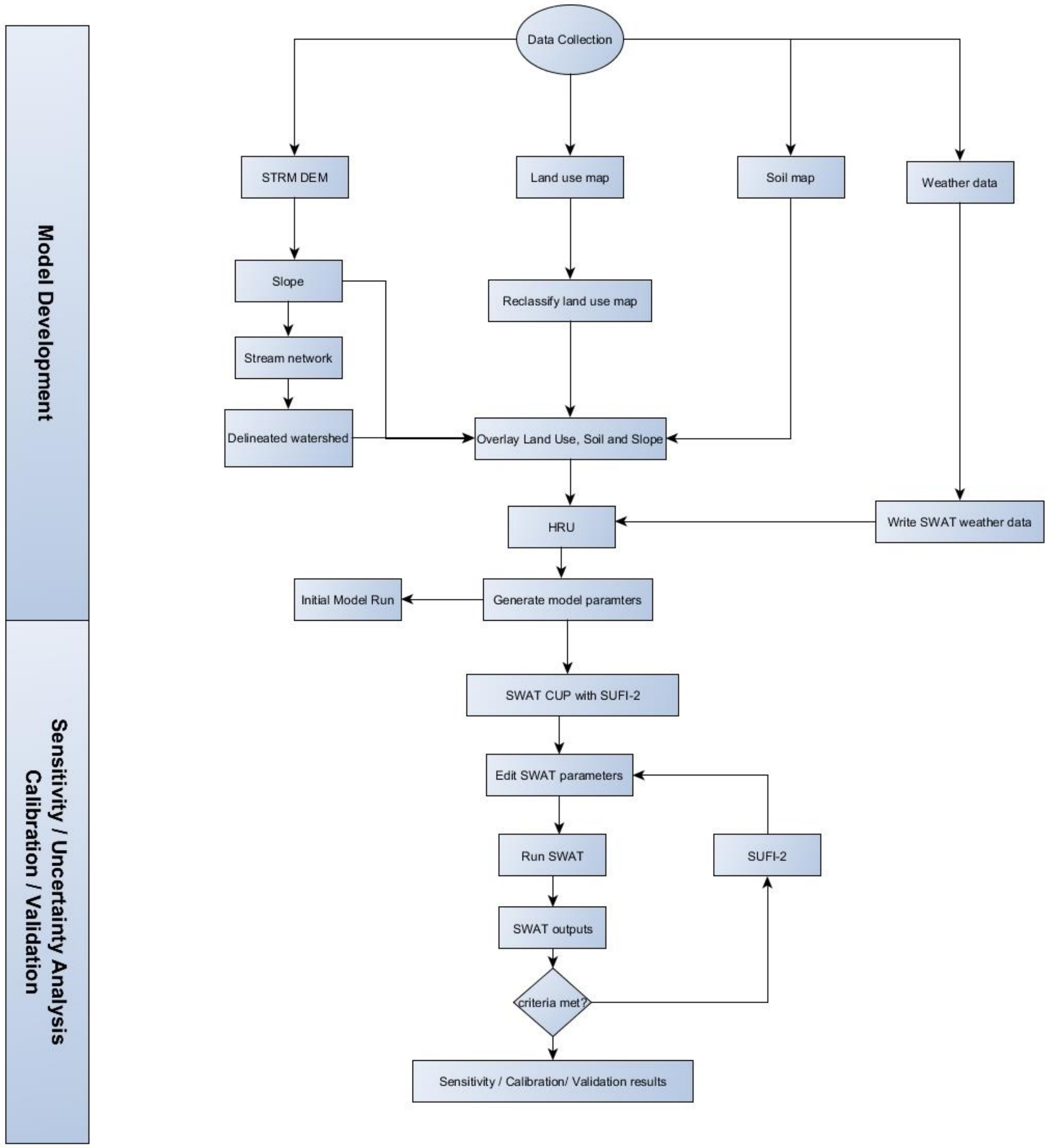


Figure 5. SWAT model development and Calibration/Validation framework for runoff simulation

In this study, we followed the calibration and sensitivity analysis protocol as suggested by (Abbaspour et al., 2015). A total of 9 SWAT parameters were selected for model calibration and uncertainty analysis for streamflow prediction based on earlier studies (Singh et al., 2013; Narsimlu et al., 2015; and Kumar et al., 2017) and SWAT documentation (Neitsch et al. 2002). The parameters selected for calibration as well as validation were Curve Number (CN), soil evaporation compensation factor (ESCO), soil available water capacity (SOL_AWC), base flow alpha factor (ALPHA_BF), groundwater revap coefficient (GW_REVAP), deep aquifer percolation coefficient (RECHRG_DP), threshold depth of water in the shallow aquifer for 'revap' to occur (REVAPMN), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN) and ground water delay (GW_DELAY).

The limit of the input values of the parameters were based on prior SWAT calibration work done in India (Singh et al., 2013; Narsimlu et al., 2015; and Kumar et al., 2017). A total of 900 simulations were executed for the 9 parameters to decide the new limits. The new values of the parameters were then utilized for the validation part. The total simulation period for the model was 22 years (1979 to 2000). A warm-up period is normally recommended to initialize and aid in the development of model variables (Tolson and Shoemaker, 2007). In this study, the first two years were used as model warm-up period to mitigate the effect of unknown initial conditions and the total simulation period was divided into two periods: calibration (1981–1990) and validation period (1991–2000).

## Results and discussion

### *Results*

Table 3 shows SWAT parameters that were included in the final calibration with their initial and final ranges, along with t-stat and p values. The comparison between the observed and computed discharge is shown in Figure **6** and Figure **7**. The calibration results (Figure **6**) revealed that the observed peak value in years 1982 and 1998 were not falling under 95PPU band. The under prediction and over prediction seen during these years could be attributed to the fact that SWAT is unable to simulate extreme events accurately and under predicts large flows in the basin (Tolson and Shoemaker, 2007). Past studies have also related over predictions and under predictions to spatial variability within a watershed (Santhi et al., 2001; Srinivasan et al., 1998). The validation results are shown in Figure **7**. During the calibration period from 1981 to 1990, the p-factor was 0.75 and the r-factor was 0.82; and for the validation period from 1991 to 2000 the p-factor and r-factor were obtained as 0.72 and 0.65, respectively.

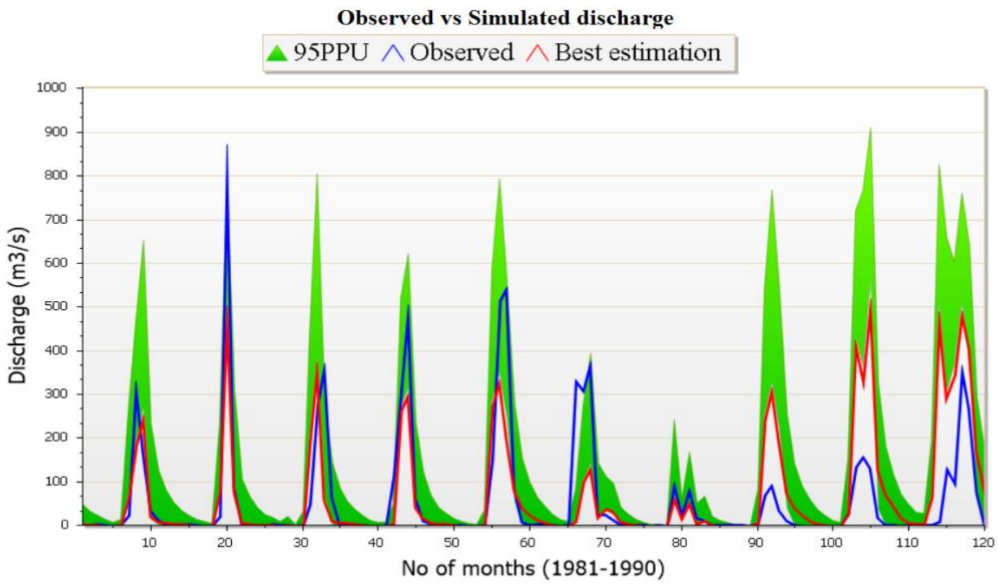


Figure 6. Observed & estimated discharges after calibration

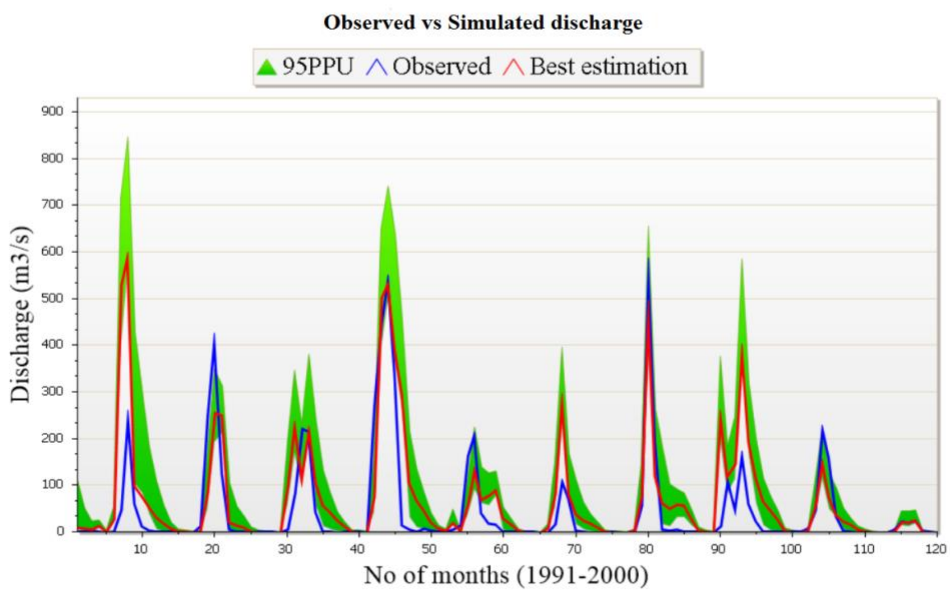


Figure 7. Observed & estimated discharges after validation

Table 3. Sensitive SWAT parameters included in the final calibration, initial and final ranges, and t-Stat and p Values

| Sl. | Parameter name | t-Stat | p-Value | Fitted_Value | Min_value | Max_value |
|---|---|---|---|---|---|---|
| 1 | v__ESCO.hru | -4.951 | 0.003 | 0.5344 | 0.4 | 0.667 |
| 2 | r__CN2.mgt | -7.248 | 0.023 | -0.099222 | -0.198 | 0.0004 |
| 3 | v__ALPHA_BF.g | -0.714 | 0.475 | 0.521667 | 0.26 | 0.782 |
| 4 | v__GW_DELAY.g | 13.984 | 0.00 | 30.35 | 0.171 | 60.53 |
| 5 | v__GW_REVAP.g | 37.592 | 0.001 | 0.196 | 0.108 | 0.284 |
| 6 | v__GWQMN.gw | 26.234 | 0.00 | 978.9 | −10.654 | 1968.43 |
| 7 | r__SOL_AWC(1).s | 12.793 | 0.00 | 0.168 | −0.0159 | 0.352 |
| 8 | v__REVAPMN.gw | 0.917 | 0.359 | 207.5 | -271.311 | 686.311 |
| 9 | v_RCHRG_DP | 3.262 | 0.001 | 0.0036 | -0.0231 | 0.03 |

v__ESCO.hru: Soil evaporation compensation factor; r__CN2.mgt: Initial SCS runoff curve; number for moisture condition II; v__ALPHA_BF.gw: Baseflow alpha factor (days); v__GW_DELAY.gw: Groundwater delay (days); v__GW_REVAP.gw: Groundwater revap coefficient; v__GWQMN.gw: Threshold depth of water in the shallow aquifer for return flow to occur (mm $H_2O$); r__SOL_AWC(1).sol: Available water capacity of the first soil layer; v__REVAPMN.gw: Threshold depth of water in the shallow aquifer for revap to occur (mm $H_2O$); v_RCHRG_DP: Deep aquifer percolation coefficient

Table 4 shows the results of sensitivity analysis. It is known that when p-value approaches zero, a parameter is taken as more sensitive for the particular analysis. When p-value approaches one, the parameter will be less sensitive. From the Table 4, it is understood that except the parameters like Alpha_BF, RECHRG_DP and REVAPMN, all the other parameters are more sensitive, and the parameter CN is the most sensitive for this sub-basin.

When a sharp and clear peak is observed for a parameter, it can be treated as a parameter with highest likelihood. Similarly, the insensitive parameters were obtained by diffused peak represented by cumulative distributions, which in turn indicate that parameter was less skilled in discharge prediction in Ong river basin. The results indicate that, most of the observations with different parameters are bracketed by the 95PPU, demonstrating that SUFI-2 was capable of capturing the model behavior.

The SWAT simulations results look satisfactory for the prediction of discharge, and the final parameter ranges were the best solution obtained for the Ong river basin. Most of the observed values during the calibration and validation were within the boundaries of

95PPU, which indicate that SWAT model uncertainties were falling within the permissible limits. The thickness of the 95PPU bands in Figure 6 and 7 show the uncertainty associated with the model and expressed by the r-factor values of 0.82 and 0.65 during the calibration and validation periods respectively. Past studies have also reported large values of r-factors for determining uncertainty in SWAT models for watersheds with high spatial variability ( Abbaspour et al., 2007 and Kumar et al., 2017).

Table 4. Sensitivity Analysis of calibrated and validated parameters

| **Parameter Name** | **Calibration** | | **Validation** | |
|---|---|---|---|---|
| | **t-Stat** | **P-Value** | **t-Stat** | **P-Value** |
| RCHRG_DP | 1.07 | 0.29 | 3.262 | 0.001 |
| ESCO | -3.18 | 0.00 | -4.951 | 0.000 |
| REVAPMN | -3.19 | 0.00 | 0.917 | 0.359 |
| ALPHA_BF | -3.54 | 0.00 | -0.714 | 0.475 |
| SOL_AWC | 7.14 | 0.00 | 12.793 | 0.000 |
| GW_REVAP | 18.58 | 0.00 | 37.592 | 0.000 |
| GW_DELAY | 19.17 | 0.00 | 13.984 | 0.000 |
| GWQMN | 25.53 | 0.00 | 26.234 | 0.000 |
| CN2 | -26.58 | 0.00 | -7.248 | 0.000 |

The percentage of observed data being bracketed by 95PPU during calibration was 75 % and during validation 72 %, which indicates a good performance of the model (Figure **6**). Uncertainties in input data and spatial variability of the basin could have caused the reduction in 95PPU (p-factor) from 0.75 to 0.72 during the validation period (Figure **7**). However, during validation, the *r* factor was found to reduce significantly, i.e., from 0.82 to 0.65, indicating a good capability of the model in the Ong river basin. In this basin, parameters dealing with lesser understood processes, such as subsurface flows and the interactions between groundwater and rivers became dominant, therefore it was interesting to note that the observed data did not fall within the 95PPU band for baseflow (Figures 6 and 7). A number of parameters affecting subsurface water were sensitive for the model which showed that subsurface flow processes were dominant in the Ong river basin which in turn added to the uncertainty in models and also affected the calibration results (Abbaspour et al., 2007). It should also be noted that SWAT does not simulate sufficiently accurate groundwater flows (Rostamian et al., 2008). Some of the other probable reasons for low performance at some parts of the model could be attributed to gridded rainfall data and the observed flow data which was rationalized as per the area ratio to obtain flow at the basin outlet. However, the calibration and validation results for the model were deemed to be satisfactory as per other studies conducted in India (Kumar et al., 2017 and Narsimlu et al., 2015).

*Comparison with other SWAT modeling studies in India*

Shinde et al. (2017) used SWAT model to analyze hydrological impacts of mining activities in the Olidih watershed in the state of Jharkhand, the neighboring state of Orrisa where this study was conducted. The results reported in this study shows similarities with the results of our study. CN and GWQMN were found to be most sensitive paramaters for this study. Inconsistency of rainfall and spatial variability was attributed to underprediction and overprediction of streamflow. Tolson and Shoemaker (2007) have also reported the inability of SWAT to simulate extreme events and over-predict and under-predict large flow events. Another study (Suryavanshi et al., 2017) conducted a hydrological analysis in the Betwa river basin in Madhya Pradesh using SWAT model. CN and GWQMN were again found to be most sensitive parameters for this basin. They also reported underprediction and overprediction of runoff. The SWAT model was found to simulate hydrology in this agriculture dominated watershed.

Kumar et al. (2017) performed hydrological modeling in another agriculture dominated watershed, the Tons river basin in the state of Madhya Pradesh. They calibrated and validated a SWAT model and reported p-factor and r-factor values of 0.54 and 0.76 respectively during the calibration period and p-factor and r-factor values of 0.68 and 0.56 respectively. Another study (Narsimlu et al., 2015) which was conducted in the Kunwari river basin in India reported p-factor and r-factor values of 0.82 and 0.76 respectively for the calibration period and p-factor and r-factor values of 0.71 and 0.72 respectively for the validation period.

*Extension for further analysis*

The model setup in this study can be used to determine the nutrients and sediment runoff potential in Ong river basin. The model is already calibrated for hydrology and since nutrients and sediment yield analysis depends largely on the ability of SWAT to simulate hydrological events, the current model has the potential to determine land use and land cover changes impacts in the basin. Being an agriculture dominated basin, crop management data can be supplied to the model to determine impacts of different crops on the water quality of this basin. Many studies in the past have employed SWAT model to simulate best management practices in various watersheds across the world (Arabi et al., 2006; Parajuli et al., 2008 and Xie et al., 2015). Since, agriculture dominated basins suffer mostly from non-point source problems, such models can prove to be useful for watershed managers to make informed decisions and aid in better watershed management.

*Limitations*

Although SWAT model has been widely applied across the world to understand hydrology, land use management, water quantity and quality analyses, some limitations have also been reported by researchers. Singh and Kumar (2017) pointed out some challenges pertaining to scale issues in input data used for modeling and their impacts on modeling results. Limited availability of input data poses another challenge for modeling studies. In this study, discharge data at Salebhata gauging site were obtained for the period 1979-2000 and were increased in area-ratio to obtain discharge at the outlet of the Ong sub-basin. To gain more confidence in the results and better parameterize the model, observed data at multiple sites or comparison with field measurements can be done in the future.

Uncertainty in hydrological model is another factor that can be present in any model due to process simplification, processes left unaccounted in a model and unknown to a modeler (Abbaspour et al., 2007). In SUFI-2 algorithm of SWAT CUP, parameter uncertainty accounts for all sources of uncertainties and the degree to which these uncertainties are accounted is reported by the p-factor which is the 95PPU (Abbaspour, et al., 2007).

In this study, we found that SWAT model was slightly inefficient in prediction of large and low flows. Spatial variability of the watershed, and parameters dealing with subsurface flows and interaction between groundwater and rivers became dominant in the watershed, therefore it was found that the observed data did not fall within the 95PPU band for baseflow simulations.

**Conclusions**

The overarching goal of this study was to develop a SWAT model for the Ong river basin for prediction of runoff after its successful calibration and validation. The period of simulation was from 1979 to 2000. The SUFI-2 algorithm built in SWAT-CUP was used for sensitivity analysis, calibration, validation and uncertainty analysis.

For hydrological prediction, such as discharge, a careful model calibration is required for an efficient result. Comparison with an additional period of data is required to validate the model and demonstrate its capability. An estimation of model uncertainties gives confidence in the use of results and model for further analysis. The following conclusions are drawn from this study.

- It is found that the parameters - CN, ESCO, SOL_AWC, ALPHA_BF, GW_REVAP, RECHRG_DP, REVAPMN, GWQMN, and GW_DELAY are the sensitive parameters for Ong river basin. Out of which, the parameter CN is the most sensitive and Alpha_BF, RECHRG_DP and REVAPMN are the least sensitive parameters.
- The percentage of observed data being bracketed by 95PPU during calibration was 75 % and during validation 72 %, which indicates a good performance of the model. Interestingly, the r-factor is found significantly reduced from 0.82 to 0.65, which is again a good indicator for model's applicability.
- The results indicate that, most of the observations with different parameters are bracketed by the 95PPU, signifying that SUFI-2 is capable of capturing the model behaviour for Ong river basin.

  The outcomes of sensitivity and uncertainty analysis using SWAT and SUFI-2 indicate that the SWAT model is appropriate for streamflow prediction in the Ong river basin. Since the model is calibrated for flow, it can further be calibrated and validated for nutrients and sediments which can make it more useful for prediction of land use and land cover change impacts on water quality in the Ong river basin. Future climate scenarios can also be analysed using the model which can help in risk assessment of floods and droughts. The results of this study can be used by watershed managers to make more informed decisions and aid in better watershed management.

**References**

1. Abbaspour K, Johnson C, van Genuchten MT (2004) Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone J,* 3, 1340–1352.
2. Abbaspour K, Vejdani M, Haghighat S (2007) SWAT-CUP calibration and uncertainty programs for SWAT. In: MODSIM 2007 International Congress on Modelling and Simulation, Modelling and Simulation Society of Australia and New Zealand, 2007
3. Adelman HM, Haftka RT (1986) Sensitivity analysis of discrete structural systems. *AIAA J*, 24(5), 823–832.
4. Arabi, M., Govindaraju, R. S., Hantush, M. M., & Engel, B. A. (2006). Role of watershed subdivision on modeling the effectiveness of best management practices with SWAT. *JAWRA Journal of the American Water Resources Association*, *42*(2), 513-528.
5. Arnold J, Allen P (1996) Estimating hydrologic budgets for three Illinois watersheds. *Journal of Hydrology*, 176, 57–77.
6. Arnold JG, Srinivasan R, Muttiah RS, Williams JR (1998) Large area hydrologic modeling and assessment - part I: model development. *JAWRA Journal of the American Water Resources Association*, 34, 73–89.
7. Batelis SC, Nalbantis I (2014) Potential effects of forest fires on streamflow in the Enipeas river basin, Thessaly, Greece. *Environ Process* 1(1), 73–85.
8. Baymani-Nezhad M, Han D (2013) Hydrological modeling using effective rainfall routed by the Muskingum method (ERM). *J Hydroinf*, 15(4), 1437–1455.
9. Beck M (1987) Water quality modeling: a review of the analysis of uncertainty. Water Resour Res 23:1393–1442 Bekele EG, Nicklow JW (2007) Multi-objective automatic calibration of SWAT using NSGA-II. *J Hydrol*, 341, 165–176.
10. Beven K, Binley A (1992) The future of distributed models: model calibration and uncertainty prediction. *Hydrol Process*, 6, 279–298.

11. Blasone R-S, Madsen H, Rosbjerg D (2008) Uncertainty assessment of integrated distributed hydrological models using GLUE with Markov chain Monte Carlo sampling. *J Hydrol*, 353,18–32.
12. Blöschl G, Sivapalan M (1995) Scale issues in hydrological modelling: a review. *Hydrol Process*, 9, 251–290.
13. Blower S, Dowlatabadi H (1994) Sensitivity and uncertainty analysis of complex models of disease transmission: an HIV model, as an example. International Statistical Review/Revue Internationale de Statistique, 229–243.
14. Chaubey, I., A. Cotter, T. Costello, and T. Soerens. 2005. Effect of DEM data resolution on SWAT output uncertainty. Hydrological Processes 19(3): 621-628.
15. Derwent R, Hov Ø (1988) Application of sensitivity and uncertainty analysis techniques to a photochemical ozone model. J Geophys Res 93:5185–5199
16. Duan Q, Schaake J, Andreassian V, Franks S, Goteti G, Gupta HV, Gusev YM, Habets F, Hall A, Hay L, Hogue T, Huang M, Leavesley G, Liang X, Nasonova ON, Noilhan J, Oudin L, Sorooshian S, Wagener T, Wood EF (2006) Model parameter estimation experiment (MOPEX): an overview of science strategy and major results from the second and third workshops. J Hydrol 320:3–17
17. Eckhardt K, Arnold J (2001) Automatic calibration of a distributed catchment model. J Hydrol 251:103–109
18. Fiseha B, Setegn S, Melesse A, Volpi E, Fiori A (2014) Impact of climate change on the hydrology of upper Tiber River Basin using bias corrected regional climate model. Water Resour Manag 28: 1327–1343
19. Gosain A, Rao S, Basuray D (2006) Climate change impact assessment on hydrology of Indian river basins. Curr Sci 90:346–353
20. Gupta HV, Beven KJ, Wagener T (2006) Model calibration and uncertainty estimation. Encycl Hydrol Sci 11:131.
21. Kumar, N., Singh, S.K., Srivastava, P.K., Narsimlu, B. (2017). SWAT Model calibration and uncertainty analysis for streamflow prediction of the Tons River Basin, India, using Sequential Uncertainty Fitting (SUFI-2) algorithm. Model. Earth Syst. Environ., Vol. 3, pp.1-13.

22. Legates DR, McCabe GJ (1999) Evaluating the use of goodness of fit measures in hydrologic and hydroclimatic model validation. Water Resour Res 35:233–241
23. Leh, M. D., Sharpley, A. N., Singh, G., & Matlock, M. D. (2018). Assessing the impact of the MRBI program in a data limited Arkansas watershed using the SWAT model. Agricultural water management, 202, 202-219. doi: https://doi.org/10.1016/j.agwat.2018.02.012
24. Mishra SK, Singh V (2003) Soil conservation service curve number (SCS-CN) methodology. Vol 42. Springer 516p
25. Narsimlu B, Gosain AK, Chahar BR (2013) Assessment of future climate change impacts on water resources of upper Sind river basin, India using SWAT model. Water Resour Manag 27:3647–3662.doi:10.1007/s11269-013-0371-7.
26. 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. Environ. Process., Vol. 2, pp. 79–95.
27. Neitsch SL, Arnold JG, Kiniry J, Srinivasan R, Williams JR (2002) Soil and water assessment tool user manual. Texas Water Resources Institute, College Station, TWRI Report TR-192
28. Neitsch SL, Arnold J, Kiniry J, Williams J, King K (2005) Soil and water assessment tool theoretical documentation version 2005 Texas, USA
29. Parajuli, P. B., Nelson, N. O., Frees, L. D., & Mankin, K. R. (2008). Conservation Effects Assessment Using SWAT in Cheney Lake Watershed CEAP South-central Kansas. In *2008 Providence, Rhode Island, June 29–July 2, 2008* (p. 1). American Society of Agricultural and Biological Engineers.
30. Patel D, Srivastava P (2013) Flood hazards mitigation analysis using remote sensing and GIS: correspondence with town planning scheme. Water Resour Manag 27:2353–2368. doi:10.1007/ s11269-013-0291-6
31. Patel DP, Srivastava PK (2014) Application of geo-spatial technique for flood inundation mapping of low lying areas. In: Remote Sensing Applications in Environmental Research. Springer, pp 113–130

32. Patel DP, Gajjar CA, Srivastava PK (2013) Prioritization of Malesari mini-watersheds through morphometric analysis: a remote sensing and GIS perspective. Environ Earth Sci 69:2643–2656
33. Paudel D, Krishna Thakur J, Kumar Singh S, Srivastava PK (2014) Soil characterization based on land cover heterogeneity over a tropical landscape: an integrated approach using earth observation datasets. Geocarto Int:1–55
34. Rosenthal W, Hoffman D (1999) Hydrologic modelings/GIS as an aid in locating monitoring sites. Trans ASAE 42:1591–1598
35. Rostamian R, Jaleh A, Afyuni M, Mousavi SF, Heidarpour M, Jalalian A, Abbaspour KC (2008) Application of a SWAT model for estimating runoff and sediment in two mountainous basins in central Iran. Hydrol Sci J 53: 977–988
36. Santhi C, Srinivasan R, Arnold JG, Williams J (2006) A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. Environ Model Softw 21:1141–1157.
37. Santhi, C., Arnold, J. G., Williams, J. R., Dugas, W. A., Srinivasan, R., & Hauck, L. M. (2001). Validation of the SWAT model on a large river basin with point and nonpoint sources. Journal of the American Water Resources Association, 37 (5), 1169-1188.
38. Shinde, V.T., Tiwari, K.N., Singh, M., and Uniyal, B., (2017). Impact of Abandoned Opencast Mines on Hydrological Processes of the Olidih Watershed in Jharia Coalfield, India. Environ. Process. Volume 4(3), pp. 697–710.
39. Singh, G. (2012). A Watershed Scale Evaluation of Selected Second Generation Biofeedstocks on Water Quality. MS Thesis. Fayetteville, AR: University of Arkansas, Department of Biological and Agricultural Engineering. Available at https://search.proquest.com/openview/6b24eb6aac6c577f8f7876dd6a46c11a/1?pqorigsite=gscholar&cbl=18750&diss=y
40. Singh, V., Bankar, N., Salunkhe, S.S., Bera, A.K., and Sharma, J.R. (2013). Hydrological stream flow modelling on Tungabhadra catchment: parameterization and uncertainty analysis using SWAT CUP. Current science, Vol., 104(9), pp.1187-1199.
41. Singh, G., & Leh, M. (2018). Setting Up a Computer Simulation Model in an Arkansas Watershed for the MRBI Program, Water and Sustainability, Prathna Thanjavur

Chandrasekaran, IntechOpen, DOI: 10.5772/intechopen.80902. Available from: https://www.intechopen.com/books/water-and-sustainability/setting-up-a-computer-simulation-model-in-an-arkansas-watershed-for-the-mrbi-program

42. Singh, G., & Kumar, E. (2017). Input data scale impacts on modeling output results: A review. Journal of Spatial Hydrology, 13(1).
43. Singh, G. & Saraswat, D. (2016). Development and evaluation of targeted marginal land mapping approach in SWAT model for simulating water quality impacts of selected second generation biofeedstock. Environ. Modelling & Software, 81, 26-39. doi: https://doi.org/10.1016/j.envsoft.2015.12.001
44. Singh, G., Saraswat, D., & Sharpley, A. (2018). A sensitivity analysis of impacts of conservation practices on water quality in L'Anguille River Watershed, Arkansas. Water, 10(4), 443. doi: https://doi.org/10.3390/w10040443
45. Singh S, Srivastava P, Gupta M, Thakur J, Mukherjee S (2014) Appraisal of land use/land cover of mangrove forest ecosystem using support vector machine. Environ Earth Sci 71:2245–2255. doi:10.1007/s12665-0132628-0.
46. Sophocleous M (2002) Interactions between groundwater and surface water: the state of the science. Hydrogeol J 10:52–67
47. Spruill C, Workman S, Taraba J (2000) Simulation of daily and monthly stream discharge from small watersheds using the SWAT model. Trans ASAE 43:1431–1439
48. Srinivasan, R., Ramanarayanan, T. S., Arnold, J. G., & Bednarz, S. T. (1998). Large area hydrologic modeling and assessment part II: model development. J. American Water Res. Assoc., 34(1), 91-101.
49. Srinivasan R, Zhang X, Arnold J (2010) SWAT ungauged: hydrological budget and crop yield predictions in the Upper Mississippi River Basin. Trans ASABE 53:1533–1546
50. Srivastava P, Mukherjee S, Gupta M (2008) Groundwater quality assessment and its relation to land use/land cover using remote sensing and GIS. Proceedings of International Groundwater Conference on Groundwater Use - Efficiency and Sustainability: Groundwater and Drinking Water Issues, Jaipur, India:19–22
51. Srivastava PK, Han D, Ramirez MR, Bray M, Islam T (2012) Selection of classification techniques for land use/ land cover change investigation. Adv Space Res 50:1250–1265

52. Srivastava PK, Han D, Ramirez MR, Islam T (2013a) Appraisal of SMOS soil moisture at a catchment scale in a temperate maritime climate. J Hydrol 498:292–304
53. Srivastava PK, Han D, Ramirez MR, Islam T (2013b) Machine learning techniques for downscaling SMOS satellite soil moisture using MODIS land surface temperature for hydrological application. Water Resour Manag 27:3127–3144
54. Srivastava PK, Han D, Rico-Ramirez MA, Al-Shrafany D, Islam T (2013c) Data fusion techniques for improving soil moisture deficit using SMOS satellite and WRF-NOH land surface model. Water Resour Manag 27: 5069–5087
55. Srivastava PK, Han D, Rico-Ramirez MA, Islam T (2013d) Sensitivity and uncertainty analysis of mesoscale model downscaled hydro-meteorological variables for discharge prediction. Hydrol Process. doi:10.1002/ hyp.9946
56. Srivastava PK, Han D, Rico-Ramirez MA, O'Neill P, Islam T, Gupta M (2014) Assessment of SMOS soil moisture retrieval parameters using tau–omega algorithms for soil moisture deficit estimation. J Hydrol 519(Part A):574–587. doi:10.1016/j.jhydrol.2014.07.056
57. Strayer DL, Ewing HA, Bigelow S (2003) What kind of spatial and temporal details are required in models of heterogeneous systems? Oikos 102:654–662
58. Suryavanshi, S., Pandey, A., & Chaube, U. C. (2017). Hydrological simulation of the Betwa River basin (India) using the SWAT model. Hydrological Sciences Journal, 62(6), 960-978.
59. Tang J, Yang W, Z-y L, J-m B, Liu C (2012) Simulation on the inflow of agricultural non-point sources pollution in Dahuofang reservoir catchment of Liao river. J Jilin Univ 42:1462–1468
60. Tolson BA, Shoemaker CA (2007) Cannonsville reservoir watershed SWAT2000 model development, calibration and validation. J Hydrol 337:68–86
61. Vanrolleghem PA et al (2003) A comprehensive model calibration procedure for activated sludge models. Proc Water Environ Fed 2003:210–237
62. Vrugt JA, Ter Braak CJ, Clark MP, Hyman JM, Robinson BA (2008) Treatment of input uncertainty in hydrologic modeling: doing hydrology backward with Markov chain Monte Carlo simulation. Water Resoures 44

63. Wagener T, Gupta HV (2005) Model identification for hydrological forecasting under uncertainty. Stoch Env Res Risk A 19:378–387
64. Wagener T, Wheater HS (2006) Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty. J Hydrol 320:132–154
65. Xie, H., L. Chen, and Z. Shen. 2015. Assessment of agricultural best management practices using models: Current issues and future perspectives, Water, 7, 3, 1088-1108.
66. Yadav SK, Singh SK, Gupta M, Srivastava PK (2013) Morphometric analysis of Upper Tons basin from Northern Foreland of Peninsular India using CARTSAT satellite and GIS. Geocarto Int :1–38
67. 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. J Hydrol 358:1–23
68. Yatheendradas S, Wagener T, Gupta H, Unkrich C, Goodrich D, Schaffner M, Stewart A (2008) Understanding uncertainty in distributed flash flood forecasting for semiarid regions. Water Resour Res 44:W05S19
69. Zhang X, Srinivasan R, Liew MV (2010) On the use of multi-algorithm, genetically adaptive multi-objective method for multi-site calibration of the SWAT model. Hydrol Process 24:955–969
70. Zheng Y, Keller AA (2007) Uncertainty assessment in watershed-scale water quality modeling and management:1. Framework and application of generalized likelihood uncertainty estimation (GLUE) approach. Water Resour Res 43: doi:10.1029/2006WR005345