

Hydrological Modeling of Mahi Basin Using SWAT

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Abstract—Hydrological modeling of river basins is a valuable tool for basin management and assessment of extreme event impacts. However, challenges with this type of modeling still remain, including issues with data acquisition, accuracy of meteorological data, model uncertainty, and operational patterns of dams/large water structure. This paper evaluates the performance and suitability of a Soil Water Assessment Tool (SWAT) model in predicting stream flow discharge, identifying sensitive parameters, and analyzing uncertainty in the Mahi river basin. This kind of assessment is useful for the hydrological community, water resources engineers involved in agricultural management and climate change concerns, as well as the government's efforts in mitigating extreme natural hazards such as droughts and floods. Since any model uncertainty becomes replicated in management practices, this paper addresses the concerns of uncertainty in hydrological modelling of Water Resources in the Mahi River Basin. A GIS environment was used to delineate the basin and its watersheds, and SWAT-CUP was used to perform the uncertainty and sensitivity analyses. The model's results were compared against five observation points spread across the basin. Statistical analysis showed that four of them resulted in good Nash–Sutcliffe model efficiency and correlation.

Keywords– SWAT; Hydrological Modelling; Mahi Basin; Uncertainty Analysis; Sensitivity Analysis; SWAT-CUP

I. INTRODUCTION

A range of models, including empirical and process-based models, has been developed for water management and watershed hydrology [1]. Great progress in watershed modeling was made as a result of advances and improvements in GIS and remote sensing [2]. Some of the watershed models developed in recent years are used to simulate the flow of chemicals, runoff, and erosion from Agricultural Management Systems [3], Erosion Productivity Impact Calculator [4], Agricultural Non-Point Source Model [5], Soil and Water Assessment Tool [6], and Hydrologic Simulation Program Fortran [7]. Among these, process-based semi-distributed models (such as SWAT) have been widely applied to evaluate the hydrologic impact of agricultural practices, dams, and climate change [9, 10, 11]. SWAT, for instance, uses the basic principles of the hydrologic cycle for simulating a basin's behavior. The SWAT model divides a basin into a number of sub-basins (here called “hydrological response units,” or HRUs) based on a combination of parameters regarding soil, land use, and slope. Similar HRUs behave and react to precipitation in similar ways. These hydrological models are highly uncertain; a deterministic approach is not a proper way to model any hydrological event. Uncertainty in prediction variable arises due to mathematical models, algorithm uncertainty, and uncertainty in input data (such as rainfall). Uncertainty in data collection is a result of measurement uncertainty. An example is uncertainty or error in measurement of stream flows. Stream flow measurements are performed through rating curves at many stream-flow-measuring sites across India. If the rating curves are not updated periodically, the uncertainty in the rating curves propagates itself in the hydrological model's uncertainty. Uncertainty in the mathematical models is well-known in modeling literature. These models use an approach to parameterize the models that require an established correlation between the modeling parameter and the physical measurement on the field and/or a natural phenomenon. For example, if a model uses Darcy's approach for infiltration, then the model must be using a certain parameter to estimate Darcy's coefficient. However, it might not be a true representation of the natural phenomenon due to externalities in nature. Porosity alone is unable to indicate the soil's moisture-retention capacity or the capacity of the soil's top layer to evaporate water. Numerical uncertainty is another significant form of model uncertainty that is currently under consideration. The model used is liable to depict uncertainty in the solution's convergence. Uncertainty due to a solution's non-uniqueness is a particular issue in hydrological models.

In general, hydrological models such as SWAT incorporate many parameters (both statistical and of physical significance). Most of these parameters obtain their values via extensive field surveys and experiments; the resulting values are then used to calibrate the model. And few of these parameters have a significant impact on the modeling results, and so they are referred to as “sensitive parameters” while others don't have much impact or very little impact. The other parameters (“insensitive parameters”) can be ignored in the mathematical model, leading to a simplification of the model's structure. Sensitivity analysis of parameters aims to explore the sensitivity of prediction variables to parameter variability. Sensitivity analysis helps reduce the number of parameters in the calibration process, while an automatic calibration technique allows the user to avoid tedious, time-consuming, manual calibration. The result is a computationally efficient calibration [19]. By including uncertainty analysis in the model parameters and output variable, more information can be conveyed about the degree of risk associated with a specific action. Uncertainty and sensitivity analyses are critical for decision-making. While calibrating the model, two concepts must be kept in mind: (1) *parameter non-uniqueness*, which states that there are many other solutions (different parameter values) that produce equally good results; and (2) *parameter conditionality*, which means that a calibrated model is only locally conditional and cannot be applied globally [2]. This paper's objective is to check the SWAT model's

performance and suitability in predicting stream flow discharge and its associated uncertainty in the Mahi river basin. Our study is relevant and useful for the hydrological community, water resources engineers involved in agricultural management and climate change concerns, and governmental efforts in mitigating extreme natural hazards such as droughts and floods.

II. STUDY AREA

The basin covers an area of nearly 3,74,842 sq. feet and lies between $72^{\circ} 21' E$ to $75^{\circ} 19' E$ and $21^{\circ} 46' N$ to $24^{\circ} 30' N$. The basin can be subdivided into two sub-basins: the Mahi upper sub-basin (65.11% of total basin area) and the Mahi lower sub-basin (34.89% of total basin area). The basin occupies an area of 15,996 Sq. km (41.73% of the total basin area) in Rajasthan, 15,474 Sq. km (40.36%) in Gujarat, and 6,866 Sq. km (17.91%) in Madhya Pradesh. A number of small tributaries (from Eru, Nori, Chap, Som, Jhakham, Moran) join the Mahi River. The average annual rainfall over the Mahi Basin is about 700 mm, and most of the rainfall occurs during the four monsoon months (June-September) [18]. As per the 2001 census of India, the total human population in the basin area is about 1,27,70,704 spreads in 15 districts [12]. There are various large dams along the reach that affect and control river flow, Fig. 1 shows below.

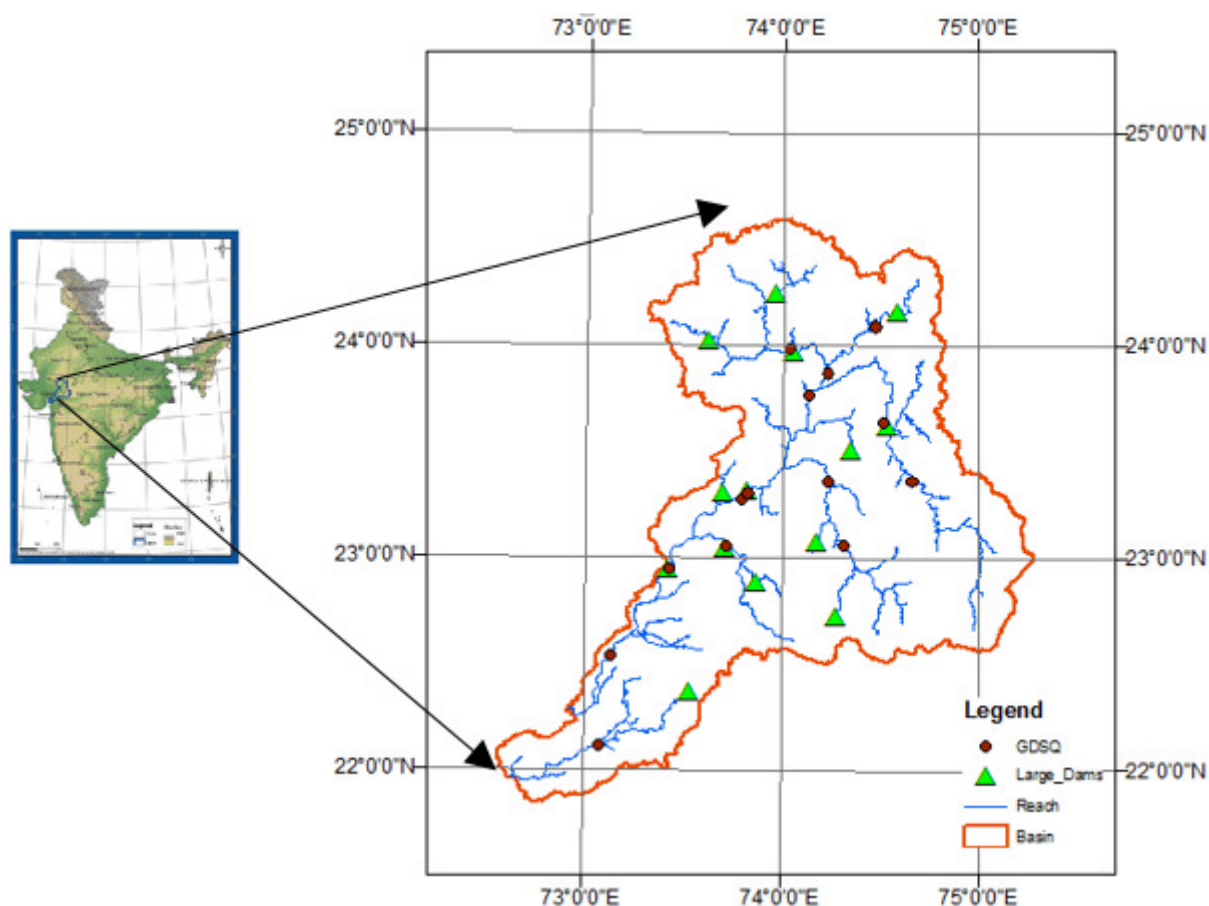


Fig. 1 Mahi Basin Index Map with Gauge Discharge sites, Large Dams, River and Basin Boundary

III. DESCRIPTION OF MODELS

A. SWAT Model

Soil and Water Assessment Tool, or SWAT, is very flexible and robust river basin hydrological model that can stimulate wide variety of watershed scenarios [8]. It is used to predict the river's stream flow, sediment, water quality, and other parameters. It is also used to model the effect of land management practices and irrigation and agricultural effect on the basin. The SWAT model requires basic meteorological data such as precipitation, soil properties, land use, land cover, and DEM. Physical processes such as infiltration, evapotranspiration associated with water movement, sediment movement, and crop growth are modeled by SWAT with the help of input data. The rainfall runoff model used by SWAT in this study is the SCS curve number model, which is described briefly below.

For modeling purposes, the river basin is divided into a number of sub-basins and then divided further into a number of HRUs (Hydrological Response Units). For every model in SWAT, the first and essential step is to model the hydrological water balance. This water balance is the driving force behind every process that happens in the river basin. A water balance equation is given as:

$$SW_f = SW_i + \sum (P_{day} - R_{surf} - Q_{seep} - E_a - D_{gw}) \quad (1)$$

Where SW_f = final water content in soil (mm water); SW_i = initial water content in soil on i day (mm water); R_{surf} = surface runoff on i day (mm water); Q_{seep} = water entering the unsaturated zone of soil on i day (mm); P_{day} = precipitation on day i (mm water); D_{gw} = return flow on day i (mm water); and E_a = amount of evapotranspiration on day i (mm water).

Fig. 2 shows a general description of the hydrological cycle. The land phase (mainly the soil layer) controls the amount of water and sediment entering the main channel in each sub-basin. A sub-basin's output is treated as input for the following sub-basin.

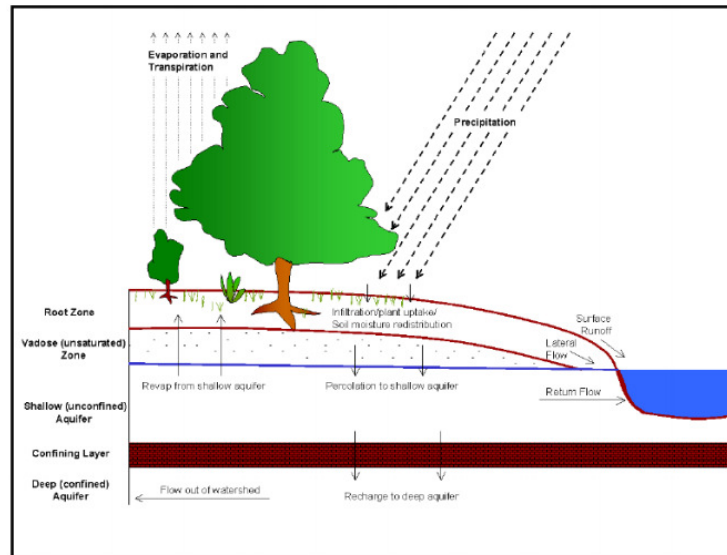


Fig. 2 Schematic representation of hydrologic cycle

After the water balance phase, the next step is the routing of water, sediments, etc. through the streams to the basin's outlet.

To calculate surface runoff, we used the SCS curve number method [13]. We used the Penman Monteith method to estimate potential evapotranspiration (PET) [14], and then actual Evapotranspiration was calculated. The SCS curve equation is described as:

$$R_{surf} = \frac{(P_{day} - 0.2S)^2}{P_{day} + 0.8S} \quad (2)$$

Where P_{day} is rainfall depth for the day (mm); Q_{surf} is accumulated runoff or rainfall excess (mm); and S is the retention parameter (mm) that can be obtained by the following:

$$S = 25.4 \left(\frac{100}{CN} - 10 \right) \quad (3)$$

The SCS curve number (CN) depends on the soil's permeability, infiltration, land use and, soil-water conditions. The CN value can be defined by three conditions: dry, average moist, and wet. A full description is available in [14] and in the SWAT technical manual [15].

B. SWAT-CUP Model

SWAT-CUP consists of a calibration and uncertainty program combined with the SWAT hydrological model. The program links many algorithms, like SUFI-2, Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), and Markov Chain Monte Carlo (MCMC) to perform uncertainty and sensitivity analyses. Parameter optimization and calibration using an inverse problem always brings uncertainty, since it starts with the results and only then calculates the parameter values causing those results. In hydrology, we perform this often – therefore, the model's results are inevitably uncertain. In this study, a sequential uncertainty fitting algorithm, referred to as SUFI-2 [23], is used for uncertainty analysis. Starting with the initial parameter ranges, SUFI-2 is iterated many times so that 95% prediction uncertainty band (95PPU) brackets most of the measured data (p factor), maintaining a small width band (r factor). Here is the step-by-step procedure to apply the SUFI-2 algorithm:

1. Decide the model's objective function. Since there is no pre-conceived, unique formulation of the objective function, this choice depends on the purpose of the study and model. Here, we used Nash-Sutcliffe Efficiency (NSE) [17] as the objective function.
2. Select the absolute meaningful range of parameters. Due to a lack of knowledge of parameter distribution, we assumed that all parameters are uniformly distributed (Gaussian distribution) within their respective range.

3. Carry out sensitivity analysis for all parameters to identify their effects on the output variable.
4. Select initial ranges for parameters in the first round of Latin Hypercube sampling. A wide range is acceptable, since it is changeable and frequently updated.
5. Perform Latin Hypercube sampling [22], resulting in n parameter combination where n represents the number of simulation trials run. This number should be large (around 1000). The algorithm iterates n times and the output variable is saved. Then, the objective function is calculated for each simulation.
6. Calculate 95PPUs of predicted/output variable (here discharge) using n Latin Hypercube simulations. After, the fit is measured for output variable from the p factor, r factor, R^2 , and NSE. Ideally, p factor should be 100% and r factor 0 – in actual circumstances, however, these numbers are near impossible. Thus, the values of p factor and r factor are accepted as around 70% and less than the standard deviation, respectively.
7. First sampling results would not, like the high value of r factor with 100% of the data, be within the 95PPU. Hence, further sampling with simultaneous updating of the parameters' ranges is needed. The newer range would be less than the original range and would be such that it reduces the initial r factor.
8. Continue procedure until the resulting parameter ranges are at the optimum range to solve the problem. Otherwise, recheck the model's structure and boundary conditions.

IV. INPUT DATA

A. Digital Elevation Model (DEM)

DEM is the raster data consisting of an array of cells or pixels containing elevation values. DEM is used to delineate the networks of river streams, sub-basins, and parameters like slopes for HRUs. Data is obtained from the Shuttle Radar Topography Mission 90m (SRTM). In the present study, DEM is projected to coordinate the system (WGS 1984 UTM Zone 43N) and the processed [values?] in a GIS environment using a watershed delineator [16]. Fig. 3 (d) shows the digital elevation map of the basin.

B. Land Use / Land Cover

The study area's land use and land cover data was obtained from the National Remote Sensing Center (NRSC), ISRO. The spatial resolution of the obtained map is 90m. We used land use and land cover data for HRU definition, and then assigned Curve Numbers (CN) to land areas for runoff calculation and hydrological analysis. Certain standard abbreviations were used for land use units (these are provided at the end of Table 1) indicated in Fig. 3 (c) the landuse/landcover map of the basin.

C. Soil Map

The study area's soil map was obtained from the National Bureau of Soil Science and Land Use Planning (NBSS&LUP). We also used the soil map for HRU definition and hydrological analysis. Fig. 3 (b) represents the soil map of the basin and Table 2 provides the standard soil codes used in the study.

TABLE 1 LAND USE DATA

| Code | LandUse/Cover |
|------|--------------------------------|
| CRDY | DRYLAND CROPLAND AND PASTURE |
| CRIR | IRRIGATED CROPLAND AND PASTURE |
| MIXC | MIXED DRYLAND/IRRIGATED CROPL |
| CRGR | CROPLAND/GRASSLAND MOSAIC |
| CRWO | CROPLAND/WOODLAND MOSAIC |
| GRAS | GRASSLAND |
| SHRB | SHRUBLAND |
| MIGS | MIXED GRASSLAND/SHRUBLAND |
| SAVA | SAVANNA |
| FODB | DECIDUOUS BROADLEAF FOREST |
| FODN | DECIDUOUS NEEDLELEAF FOREST |
| FOEB | EVERGREEN BROADLEAF FOREST |
| FOEN | EVERGREEN NEEDLELEAF FOREST |
| FOMI | MIXED FOREST |
| WATB | WATER BODIES |
| WEHB | HERBACEOUS WETLAND |
| WEWO | WOODED WETLAND |
| BSVG | BAREN OR SPARSLY VEGETATED |
| TUHB | HERBACEOUS TUNDRA |
| TUWO | WOODED TUNDRA |
| TUMI | MIXED TUNDRA |
| TUBG | BARE GROUND TUNDRA |
| ICES | SNOW OR ICE |

TABLE 2 NBSS SOIL CODE

| Soil Code | Hydrological Group | Soil Type |
|----------------|--------------------|-----------------|
| Ao81-2b-3652 | D | LOAM |
| Be75-2a-3676 | C | LOAM |
| Be76-2b-3677 | D | LOAM |
| Bv12-3b-3696 | D | CLAY_LOAM |
| I-Be-Lc-b-3716 | C | LOAM |
| Jc51-2a-3744 | D | LOAM |
| Jc51-2a-3744 | D | LOAM |
| Lc70-1-2b-3774 | C | SANDY_CLAY_LOAM |
| Vc13-2-3b-3858 | D | CLAY |
| Vc21-3a-3859 | D | CLAY |
| Vc43-3ab-3861 | D | CLAY |
| Vc45-3a-3864 | D | CLAY |
| WATER-6997 | D | WATER |

D. Meteorological Data

The principal data we used in the study was hydrological and weather data of the Mahi basin. The area's meteorological data was obtained from the Indian Meteorological Department (IMD), and the Central Water Commission (CWC), India.

E. Large Dam Details

There are approximately 15 large water resource structures that affect and control the river flow. Various details like spatial location, year of operation, and reservoir capacity (among others) need to be kept in mind when performing the hydrological study. Very limited data is available regarding the dams' operation pattern and behaviour. Fig. 3(a) offers a map showing the spatial location of the large dams.

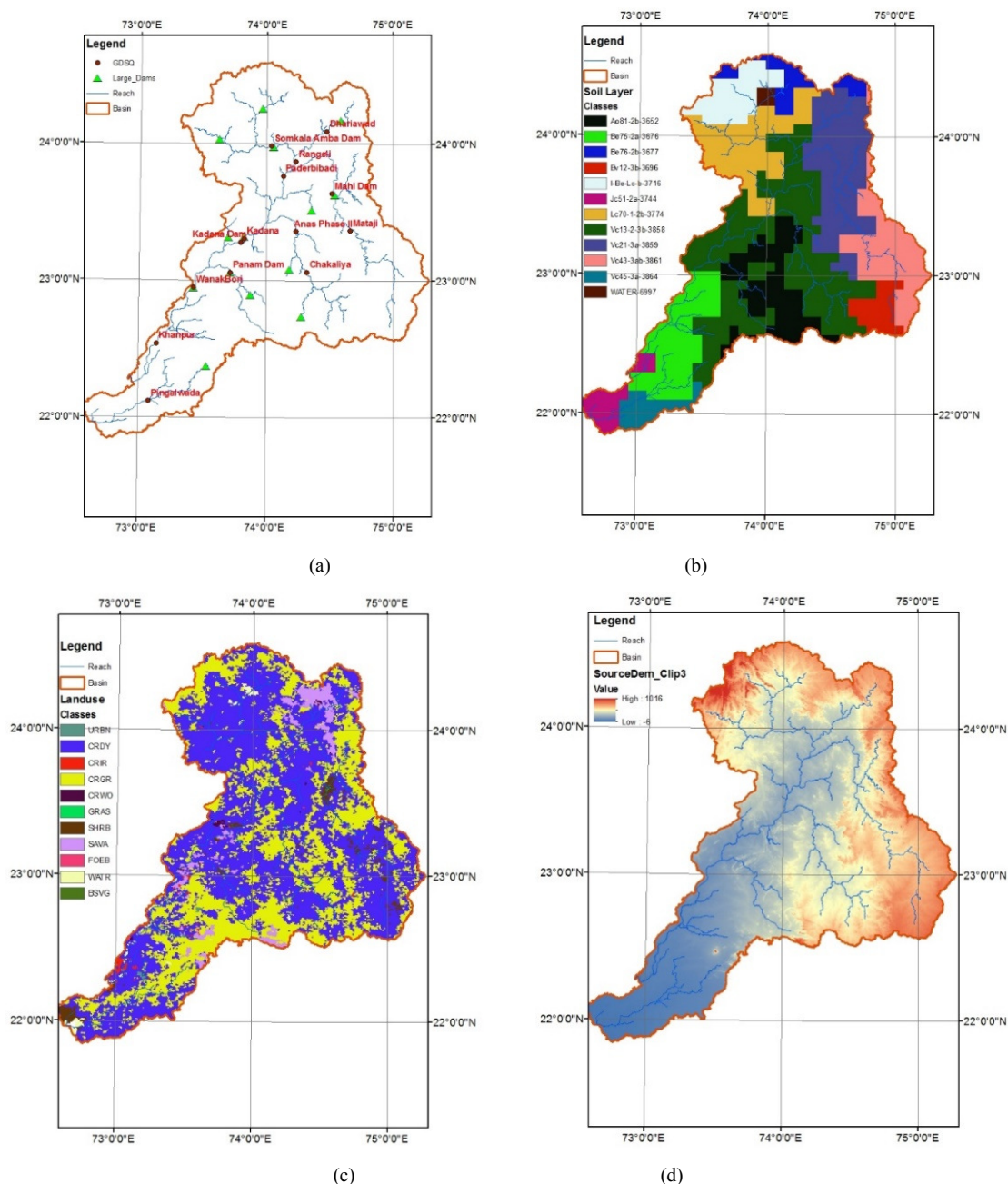


Fig. 3 Basic spatial data input to the model (a) Discharge Gauge Sediment Quality stations (GDSQ) (b) Soil map (c) Land use map (d) Digital Elevation Model (DEM)

V. MODEL SETUP

A. SWAT Model

The input data needed for the SWAT model requires the use of a Digital Elevation Model to generate slope, basin boundary, topography, land use, soil layer data and climate data. The latter includes daily precipitation values, daily minimum and maximum air temperature, and solar radiation, which can be derived using theoretical formulae, relative humidity, and wind speed. Daily precipitation and minimum and maximum temperature are entered in the model while the other parameters are simulated based on the nearest climate station using a SWAT weather generator.

The model is built completely in a GIS environment using a SWAT extension [16]. A watershed delineation tool is used to delineate the sub-basins based on DEM data. Subsequently, a stream network is also generated using DEM data. Accordingly, the basin is divided into 148 sub-basins. After this, Hydrological Response Units (HRUs) are created based on slope, land use, and soil data. HRU creation in SWAT requires land use and soil threshold inputs in order to derive HRUs. A threshold value of 10% of the basin's total area is selected. The set threshold values divide the HRUs into a number of sub-units, each with a unique ID. Areas that respond to incoming precipitation similarly are therefore areas with similar hydrological response. Runoff for individual HRUs is calculated separately and then used to obtain the total runoff. Fig. 4 below shows the workflow of the SWAT Model.

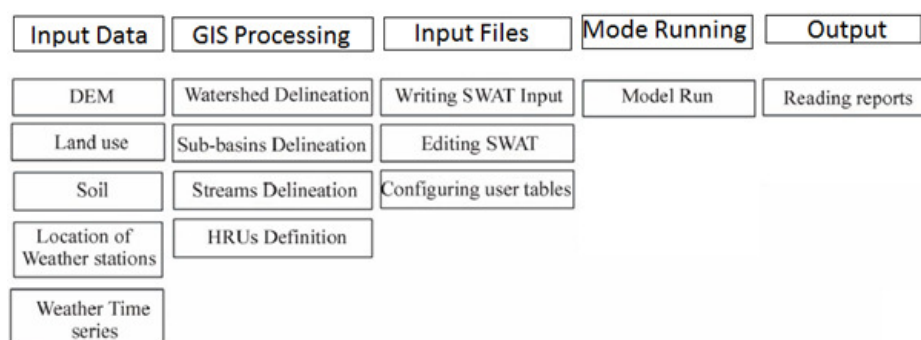


Fig. 4 Flow diagram: setting up SWAT Model

B. SWAT-CUP Model

Automated model calibration requires changes in iterations and model parameters. When the model is run, the required outputs are evaluated from model output files. The SWAT-CUP's main function is to provide a link between the model and the input and output of calibration. A schematic diagram below shows the linkage between SWAT and SWAT-CUP. The SWAT model's output is fed as input for SWAT-CUP. Fig. 5 below represents the combined workflow of SWAT and SWAT-CUP models.

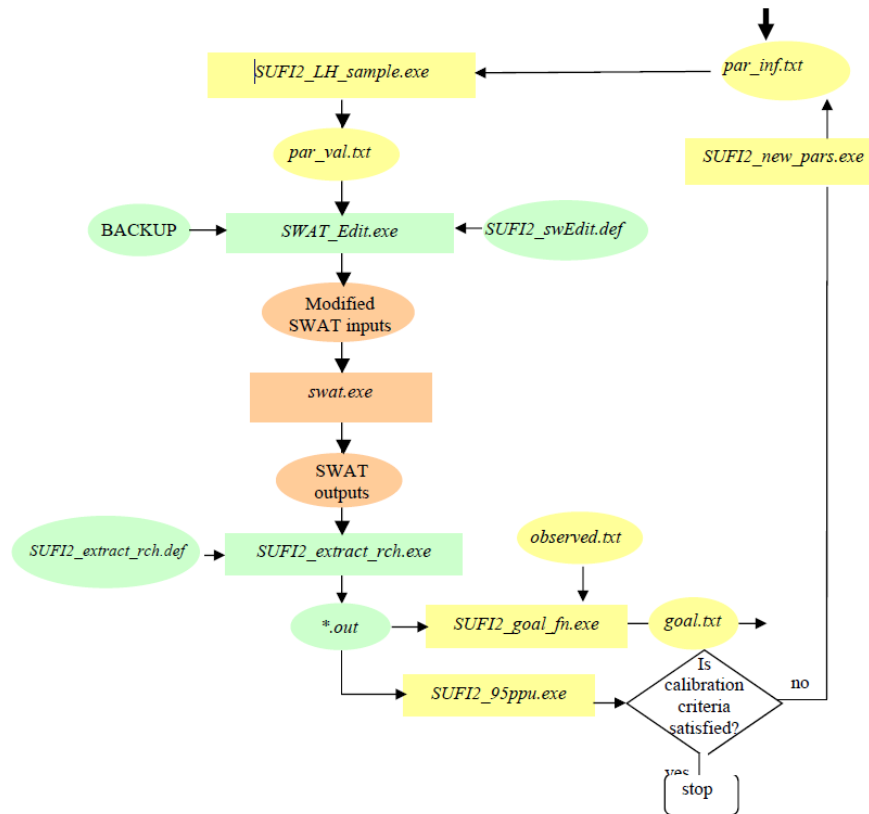


Fig. 5 Flow diagram: setting up SWAT-CUP SUFI-2 model

(Source: SWAT-CUP user manual, K.C. Abbaspour)

VI. PERFORMANCE EVALUATION

The SWAT model's performance is calculated using a graphical representation of observed and simulated discharge values, as well as on the basis of various statistical parameters such as Nash-Sutcliffe Efficiency (NSE) and coefficient of determination (R^2) [17]. We used the R^2 coefficient to evaluate the trend between observed and simulated values. The range of NSE values can vary from $-\infty$ to 1, where $NSE = 1$ is the most optimum value. NSE values from 0.6 to 1 are considered to be a good fit, whereas values less than 0 imply that the observed values' mean is a better predictor than the simulated values. The R^2 varies between -1 and 1, where 1 represents perfect positive trend and -1 represents perfect negative / opposite trend. The coefficient of determination and NSE can be calculated by the equations given below:

$$R = \frac{[\sum(Q_{m,i} - \overline{Q_m})(Q_{s,i} - \overline{Q_s})]^2}{\sum_i(Q_{m,i} - \overline{Q_m})^2 \sum_i(Q_{s,i} - \overline{Q_s})^2} \quad (4)$$

$$NSE = 1 - \frac{\sum(Q_m - Q_s)^2}{\sum(Q_m - \overline{Q_m})^2} \quad (5)$$

Where Q_m is the measured discharge value; Q_s is the simulated discharge; $Q_m(\text{bar})$ is the average measured discharge; and $Q_s(\text{bar})$ is the average discharge simulated.

We calculated uncertainty and sensitivity performance using p factor and r factor values. As established earlier, the model will be most effective if p factor is closer to 100% and r factor is less than the standard deviation. A large p factor can be achieved at an expense of a large r factor. Therefore, balancing these two factors is required, and when acceptable values of r factor and p factor are reached, the parameter uncertainties become the desired parameters. R factor can be calculated as:

$$r \text{ factor} = \frac{1}{n} \sum_{ti=1}^n \frac{Y_{ti(97.5\%)} - Y_{ti(2.5\%)}}{\text{Std}(\text{obs})} \quad (6)$$

Where $Y_{ti(97.5\%)}$ and $Y_{ti(2.5\%)}$ are the upper and lower boundaries of the 95PPU; and $\text{Std}(\text{obs})$ is the observed data's standard deviation.

VII. RESULTS AND DISCUSSIONS

A. Sensitivity Analysis

Parameter sensitivities are determined by performing a multiple regression analysis, which regresses the parameters generated by Latin Hypercube against the objective function [2]. t-test and p-value are used to identify each parameter's relative significance. The t-stat is the ratio of parameter coefficient to its standard error. Parameters with p value less than or equal to 0.05 are taken as sensitive. We found that, out of 14 total parameters, seven were sensitive to the output variable (discharge). This reduces the number of parameters for calibration. Table 3 shows the list of parameters used in sensitivity analysis and each parameter's individual sensitivity. The sensitive parameters are: SOL_AWC, SOL_K, CH_K2, GW_DELAY, CN2, ALPHA_BF, ESCO.

TABLE 3 SENSITIVITY ANALYSIS TABLE WITH T-STAT AND P-VALUE

| Abbreviated | Descriptions of parameters | t-stat | p-value | Rank |
|-------------|---|----------|-------------|------|
| SOL_AWC | Available water capacity of the soil layer. | 17.64949 | 0 | 1 |
| SOL_K | Saturated hydraulic conductivity. | -16.3289 | 0 | 2 |
| CH_K2 | Effective hydraulic conductivity in the main channel alluvium. | 3.432463 | 0.000649972 | 3 |
| GW_DELAY | Groundwater delay (days). | 2.915269 | 0.003720346 | 4 |
| CN2 | SCS runoff curve number | -2.1156 | 0.034893979 | 5 |
| ALPHA_BF | Baseflow alpha factor (days). | -2.11401 | 0.035030255 | 6 |
| ESCO | Soil evaporation compensation factor. | -1.92773 | 0.054480029 | 7 |
| CH_N2 | Manning's "n" value for the main channel. | 1.236497 | 0.216879971 | 8 |
| GW_REVAP | Groundwater "revap" coefficient. | 0.914357 | 0.360989077 | 9 |
| SOL_BD | Moist bulk density. | -0.69713 | 0.486061802 | 10 |
| GWQMN | Threshold depth of water in the shallow aquifer required for return flow to occur (mm). | -0.46446 | 0.642532698 | 11 |
| ALPHA_BNK | Baseflow alpha factor for bank storage. | -0.39213 | 0.695139901 | 12 |
| SLSUBBSN | Average slope length. | -0.35082 | 0.725878202 | 13 |
| REVAPMN | Threshold depth of water in the shallow aquifer for "revap" to occur (mm). | -0.22826 | 0.819540499 | 14 |

B. Calibration Process

Using the sensitive parameters, we carried out model calibration in a SWAT-CUP environment. Calibration is performed using observed discharge data from five stations spread across the basin with monthly time steps. This process gave us the optimum parameter ranges. Moreover, since we were doing inverse optimization, the ranges were applicable to our basin. We computed the model's performance using NSE and R^2 values. The statistical results we computed showed that most of the stations are giving good results as compared with observed values. Table 4 shows the statistical coefficients and parameter's optimum ranges. Only the Rangeli station is not giving good results in neither R^2 nor NSE coefficients. One of the possibilities for this deviation from optimum values may be that the Rangeli station lies just below several tributaries with four large dams. Due to data limitation regarding the dams' operational patterns, a large deviation from optimum at Rangeli station is observed. This might be corrected by incorporating the dams' operational patterns in the SWAT model. This limitation is due to lack of data availability for the Rangeli dam. Additionally, this is a scale issue in Hydrology. The scale at which modeling is performed also gives rise to uncertainty in Hydrological models.

TABLE 4 STATISTICAL RESULTS OF THE ANALYSIS AT DIFFERENT OBSERVATION SITES

| Station Name | p-factor | r-factor | R2 | NSE | | p-factor | r-factor | R2 | NSE |
|--|----------|----------|------|------|--|---|----------|------|------|
| Rangeli | 0.34 | 1.22 | 0.69 | 0.43 | | 0.24 | 0.44 | 0.66 | 0.53 |
| Mataji | 0.65 | 0.57 | 0.86 | 0.81 | | 0.42 | 0.26 | 0.8 | 0.73 |
| Chakaliya | 0.33 | 0.22 | 0.84 | 0.58 | | 0.17 | 0.12 | 0.81 | 0.52 |
| Khanpur | 0.13 | 0.19 | 0.87 | 0.82 | | 0.13 | 0.17 | 0.89 | 0.66 |
| Pingalwada | 0.63 | 0.91 | 0.84 | 0.76 | | 0.21 | 0.35 | 0.8 | 0.75 |
| Calibration using complete parameter set | | | | | | Calibration using sensitive parameter set | | | |

C. Uncertainty Analysis in Streamflow Prediction

We derived the performance indices of uncertainty analysis for the model parameters using monthly time steps. As discussed earlier, uncertainty analysis was done using p factor and r factor. Results show the 95% prediction band (95PPU), p factor, and r factor values. The p factor and r factor values for three sites are too small. In addition, the uncertainty band did not

cover many of the observed values, although the NSE and R^2 coefficient were satisfactory. A reason behind this might be that these stations are located downstream of a few large dams. These dams capture enormous amounts of water. Due to the unavailability of the dams' operational data, SWAT is unable to capture the true discharge values. SWAT models at monthly scale with such streamflow predictions may be considered for application in Planning scale models. This may also be used for Water Resources development on a larger scale of both time and space.

Also, SWAT has the limitation that it does not thoroughly simulate groundwater flow. A careful examination shows that much of the unbracketed data in 95PPU lies in the low flow or baseflow region. Fig. 6 shows an example of such a case. If this flow had been simulated properly, then the p factor would have been much higher. NSE also has the limitation that it strongly overestimates larger values while neglecting lower values, since it calculates by squaring the differences between observed and simulated [20] therefore showing good NSE in spite of poor low flow simulation.

VIII. LIMITATIONS AND FUTURE WORK

In this study, we performed uncertainty and sensitivity analyses of model parameters. Our main objective was to improve the calibration process and achieve more accurate results. We found that calibration using sensitive parameters resulted in slightly poorer results compared to calibration using a complete set of parameters. A potential explanation might lie with the limitations of SWAT, which does not model groundwater flow properly. Our sensitivity analysis also indicated that groundwater parameters (GW_delay Alpha_bf that directly impacts groundwater flow, and Sol_AWC that indirectly affects groundwater flow) are sensitive. Future research based on this study must overcome these SWAT limitations. This can be achieved by integrating SWAT and Modflow [21] models. Modflow is a widely used model in groundwater modeling.

IX. CONCLUSIONS

A thorough model calibration is required to obtain accurate results when performing prediction using a hydrological model (such as discharge). Along with the results, it is always advisable to report model uncertainty in the model predictions. In this paper, we applied the SWAT model in the Mahi River Basin to simulate discharge in the period of 1992-2005. We did this at a monthly scale with data from large dams incorporated at a few sites. The model was then calibrated and uncertainty and sensitivity analyses were done to obtain sensitive parameters. The common SUFI-2 algorithm was employed here to carry out uncertainty and sensitivity analyses. Our study's results indicate that the SWAT and SAWT-CUP models are useful in forecasting flow and performing uncertainty and sensitivity analyses. SWAT, however, has a limitation in groundwater modeling (this is illustrated in Fig. 6, where the base flow is poorly predicted by the model). The model is at a monthly scale and it can be used to plan Mahi River Basin's future project development, as long as sufficient data and details are incorporated and the model is validated and identified. Additionally, this study's model can be used in further assessment of climate change and land use/land cover impact assessment on river basin. For improving Ground Water Modeling, SWAT-MODFLOW is a new platform that can be used for future studies of this nature.

X. GRAPHICAL REPRESENTATION OF RESULTS

A. Calibration and Uncertainty Analyses Using Complete Set of Parameters

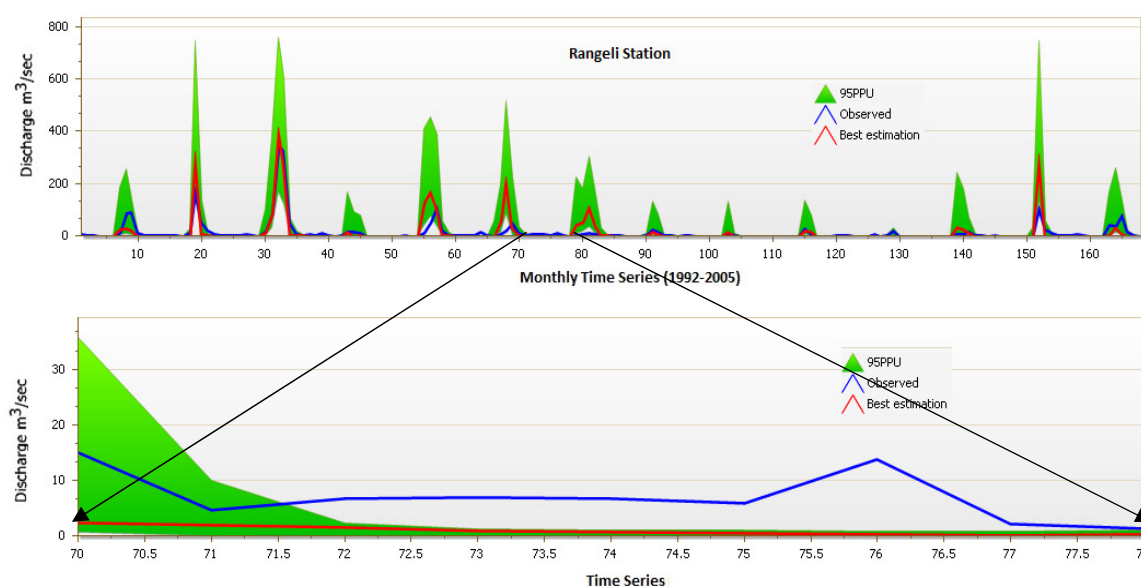
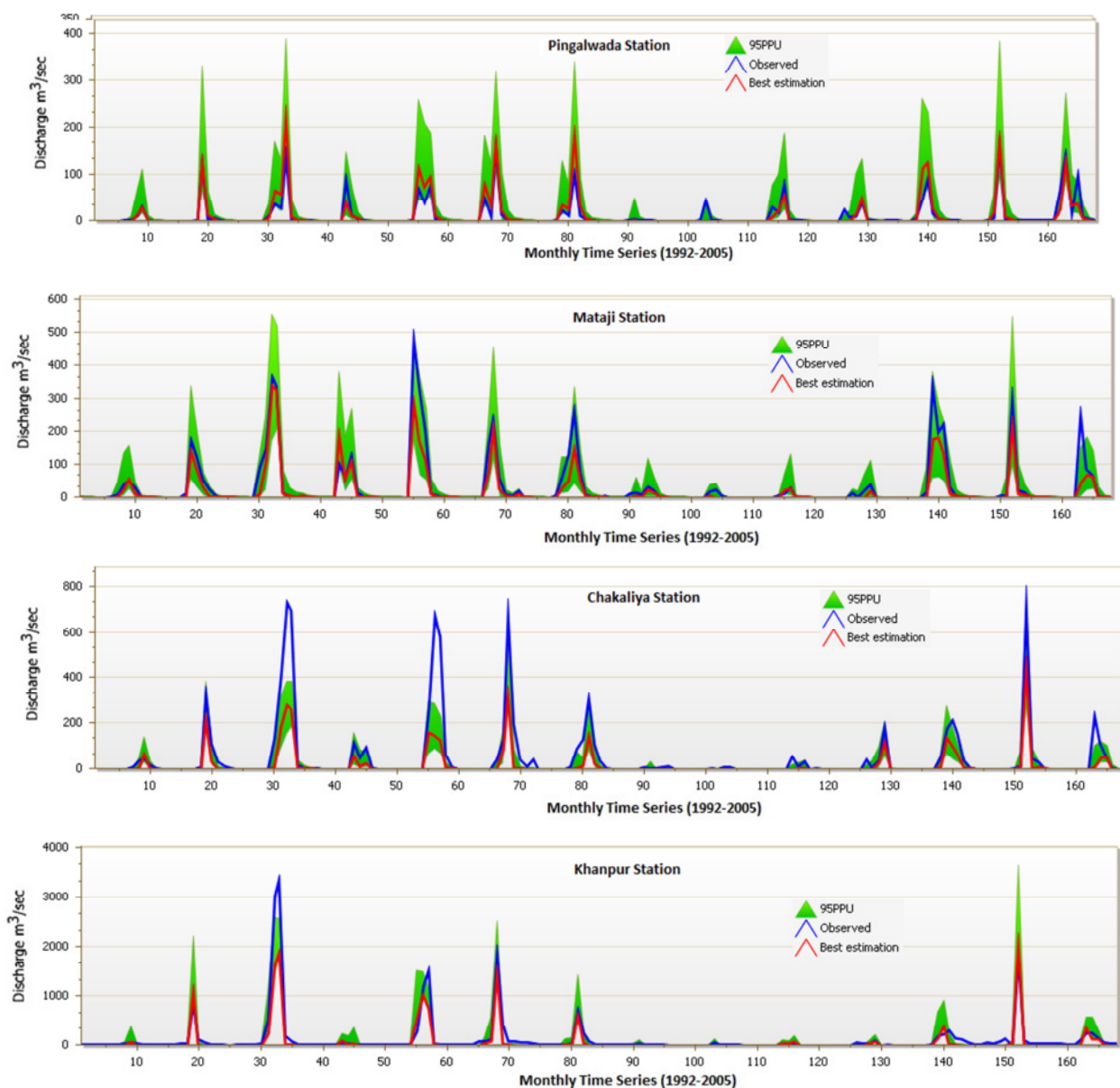
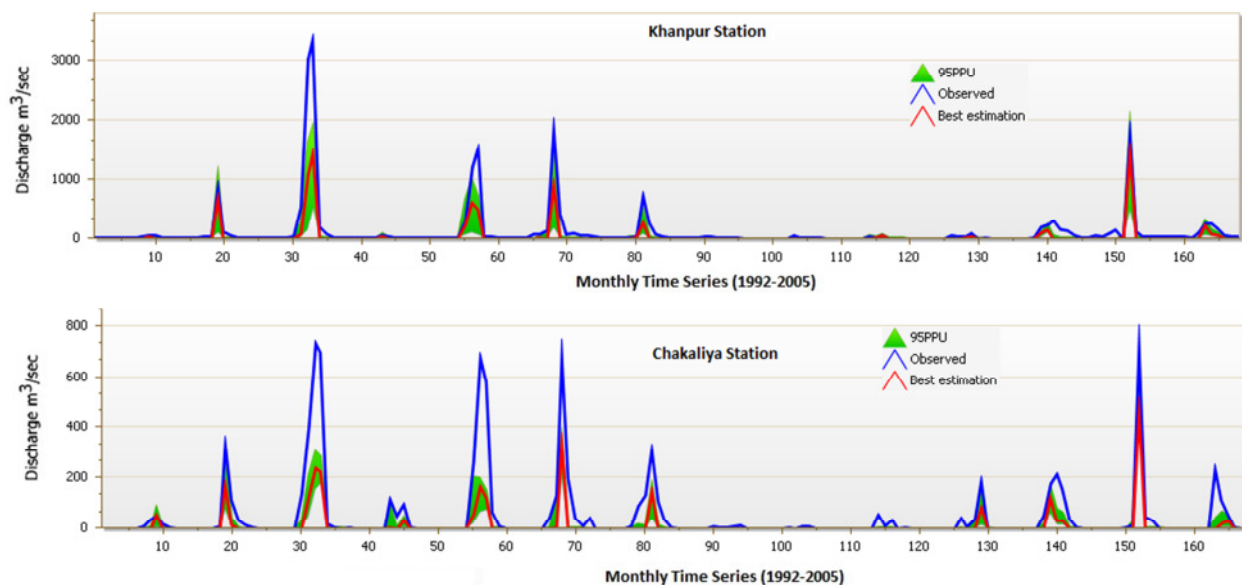
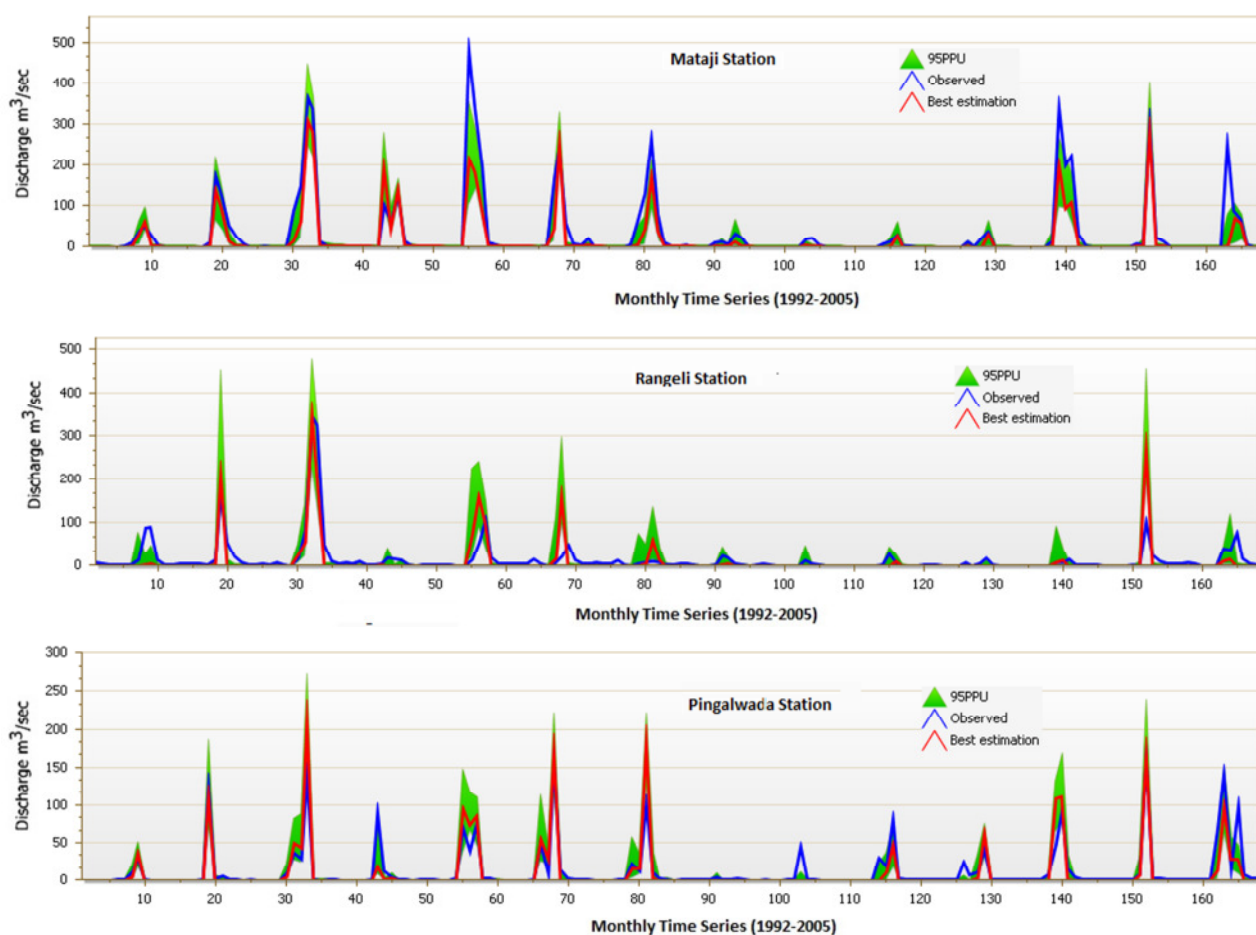


Fig. 6 showing 95PPU range not covering baseflow



B. Calibration and Uncertainty Analyses Using Only the Sensitive Set of Parameters





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