UNCERTAINTY ASSOCIATED WITH SWAT MODEL FOR THE ESTIMATION OF STREAMFLOW FOR KOSI BASIN, INDIA

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Abstract

The outputs from Hydrological models generally undergo certain uncertainties from different sources of errors (error in input parameters, model structure or due to model simplifications, unknown or non-ascertainable relations within the model). Relatively, it is easy to control parameter uncertainty through various calibration procedures. In this study an important tool called Soil and Water Assessment Tool(SWAT), which is an eco-hydrological model was used to simulate the Kosi basin. SWAT-CUP was the interface used for sensitivity analysis, model calibration and uncertainty assessment using Sufi-2 algorithm. The first 4 years (1987-90) was taken as warmup period and the period of (1987-99) was calibrated then the model was validated for the next 8 years (2000-2007). In this process, p-factor refers to the percentage of observations covered by 95PPU band while r-factor describes the average of 95PPU band width divided by the standard deviation. In calibration, the p and r factors were obtained as 0.31 and 0.22 and in validation, their values are 0.31 and 0.24 respectively. The coefficient of determination (R^2) and Nash–Sutcliffe efficiency (NSE), was used to check the goodness of fit between observed and ultimate best simulated results. The results obtained during calibration indicated R^2 and NSE values were 0.63 and 0.43 respectively. The validation also yielded satisfactory values of R^2 and NSE as 0.70 and 0.51 respectively. The output of statistical Analysis indicated a perfect match between the observed data and the best simulated data values which showed that the model was well calibrated for streamflow simulation.

Keywords: *SWAT-CUP. SUFI-2. Calibration. Validation. Objective function. Uncertainty analysis.*

1.Introduction

The models that are used to represent the simplified forms of the real world system are called Hydrologic models. These models enables extensively to predict, understand and manage water resources. Based on the design, there are many hydrologic models like simple conceptual model which assumes the basin as a single unit thus considering less parameters and comprehensive, while some spatial variability models involving more parameters thus making it complex. While using various hydrologic models, various uncertainties are observed. Hydrological systems are very complex to understand. Hence, to overcome this complexity, hydrologists used hydrological modelling in order to represent it more easily(Woessner,2012). Many mathematical models have recently incorporated the GIS application to generate inputs and display outputs or as an interface for the whole modelling process. The SWAT model is a hydrologic model that analyses the impacts, change in land use and land cover (lu&lc) and also change in climate on water resources (Narsimlu et al, 2013; Srivastava et al, 2013). In spite of numerous semi-distributed hydrological models being used all around the world, SWAT model was initially used for the estimation of streamflow from ungauged basins (Arnold et al, 1998). At present, parameter uncertainty assessment has become more popular in sciences, involving hydrological sciences (Yatheendradas et al, 2008; Beven and Binley, 1992**;** Beck ,1987); the science of atmosphere (Derwent and Hov 1988), the science of structures and biosciences (Blower and Dowlatabadi 1994). There are four algorithms for carrying out uncertainty analysis of a hydrologic model namely Parameter Solution Method (ParaSol, van Griensven and Meixner, 2006), Sequential uncertainty fitting (Sufi-2, Abbaspour et al, 2007), Markov Chain Monte Carlo (MCMC, Vrugt et al., 2003), Particle Swarm Optimisation (PSO, Eberhart and Kennedy, 1995) and Generalised Likelihood Uncertainty Estimation (GLUE, Freer et al., 1996).

Generalised Likelihood Uncertainty Estimation (GLUE) method results in response from only a few parameters and have its impact on stream flow and sedimentation, while Parameter Solution Method (ParaSol) results in well prediction of sedimentation. Particle Swarm Optimisation(PSO) can obtain better results than any other algorithm in evolutionary computation. The Sequential uncertainty fitting (Sufi-2) method is developed for the proper calibration and prediction of uncertainty. In recent years Sufi-2 method is mostly used to predict uncertainty as it can be applied to all types of sources of uncertainty. The degree of uncertainty can be measured using mainly two factors, p-factor and r-factor. The factor which indicates percentage of observed data covered by the 95% prediction uncertainty (95PPU) is said to be p-factor while r-factor describes the average 95PPU band width divided by standard deviation of the given data. The 95% prediction uncertainty (95PPU) was obtained from the cumulative distribution of the output variables at the levels of 2.5% and 97.5% respectively. A large r-factor shows the large uncertainty of parameters. A balance between these two factors is needed when decreasing parameter uncertainty (Abbaspour, 2011). Generally, it is assumed that as the r-factor value approaches to 0, the p-factor value gets closer to 1. Similarly, the percentage overlap between simulated and observed data indicates the amount of uncertainty. In this study, objective function is taken as

NSE whose value range should be less than or equal to 0.5. If the results show a relatively large p-factor with small r-factor and the value of Nash-Sutcliffe Efficiency value as in the range, the calibration is acceptable.

The purpose of this study is to perform model calibration and uncertainty prediction using Sequential Uncertainty Fitting(Sufi-2) technique with an important tool called SWAT-CUP (SWAT-Calibration and Uncertainty Programs). After analysing the sensitivity and calibrating a hydrological model, uncertainty prediction has paid much attention in recent years (Srivastava et al, 2013**;** Blasone et al, 2008**;** Zheng and Keller 2007; Wagener and Wheater 2006). This calibrated model can now be used for any further analysis of climate change and also for the prediction of impact of changes in land use/land cover(lu&lc). It is suggested that more uncertainty techniques can be used for the calibration of a hydrologic model and also for the prediction of uncertainty in future studies.

2.Description of the Study area

The Latitude and Longitude of Kosi River is 26.4517^o N and 86.8511^o E respectively. The Kosi basin is bounded by the Himalayas on the north, Mahananda basin on the east, Burhi Gandak basin on the west and river Ganga on the south. The Kosi basin in India extends over areas of districts Saharsa, Purnea, Khagaria, Madhubani, Sitamarhi, Muzaffarpur and Darbhanga in Bihar state. The Kosi river fan is one of the largest source of alluvial cones in northern part of India built by any river in the world, draining an area of 74,500 sq.km of which only 11,070 sq.km lie within India. During the past 200 years, the river has been shifting towards the westwards for a distance of about 112 Km and has built large area of agricultural land in Saharsa, Darbhanga and Purnea districts which is of no use. The total catchments area up to its outfall in the River Ganga is 100800 sq.km It is 180 km long and 150 km wide. The Kosi river is joined by many of the major tributaries in the Mahabharat Range nearly 48 km north of the Indo-Nepal border. The Kosi river has built up a megafan of about some 15,000 km^2 below the Shiwaliks. Kosi region comes under zone II and include 8 districts (Supaul, Saharsa, Madhepura, Araria, Purnia, Katihar, Khagaria, Kishanganj). In this study, SWAT is used to simulate kosi basin hydrologically. The study area and the location map in detail is as shown in detail in figure.1

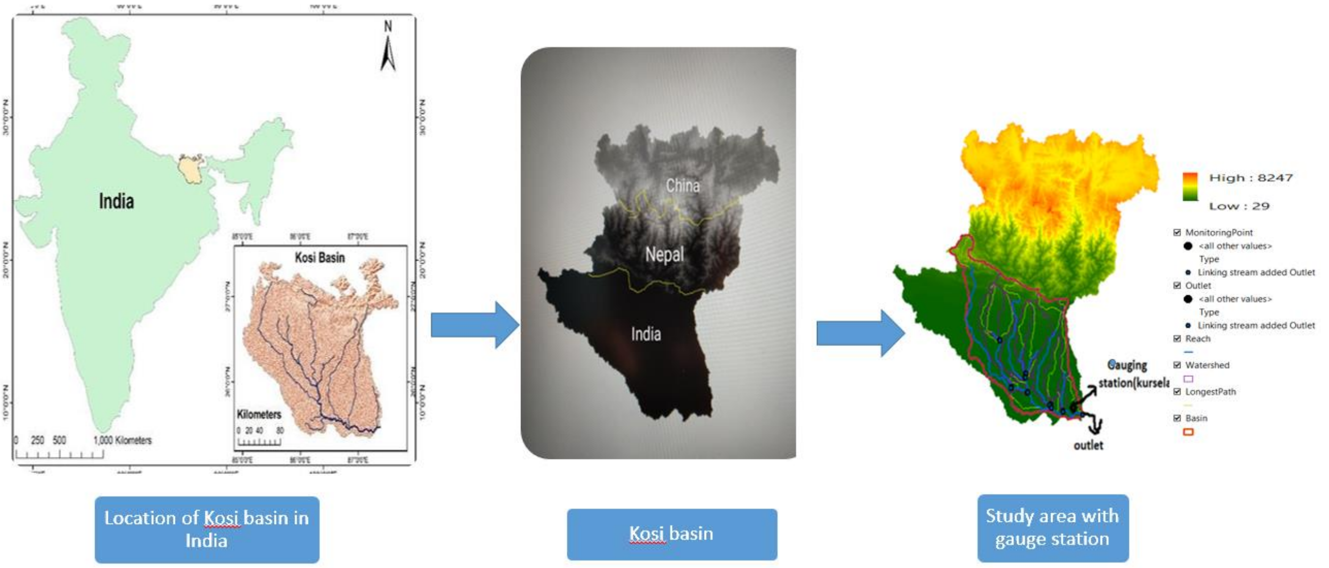

Figure 1 Location map of Kosi basin

3.MATERIALS AND METHODS

3.1 Datasets

In this study, SWAT divides the watershed area in to sub basin then sub-basins into small hydrologic response units(HRU) in the process of watershed Delineation. It helps in deriving the suitable parameters for the model. The required datasets are DEM, land use/land cover maps, geographic data, weather data and discharge data for the simulation of kosi basin as recorded in Table.1

Table.1 Details of data for kosi basin

S. No	Data related to spatial reference	Description and source of data
1.	Digital Elevation Map	Shuttle Radar Topography Mission of USGS (SRTM) (http://earthexplorer.usgs.gov/)
2.	Land use and Land cover maps	Landsat 8 & USGS (http://earthexplorer. usgs.gov/)
3.	Soils data	Food and Agricultural Organization of the United Nations soil map (FAO)
4.	Weather data	Central Water Commission (CWC)
5.	Hydrological data	Extracted from Kosi Mechi link project.

3.2 SWAT MODEL

SWAT is a process based semi-distributed hydrological model that simulates ecosystem services on the basis of daily time step. The governing equation of all the hydrological domains is the water Budget equation which describes the inflow and outflow of a system. This is explained in equation(1)

$$SW_t = SW_0 + \sum_{i=1}^{t}(R - Qs - Ea - Wseep - Qgw) \quad (1)$$

Where SW_t is the final water content of soil(mm); SW_0 - water content of soil initially on i^{th} day (mm); R –Precipitation on i^{th} day (mm); Qs - Surface runoff on i^{th} day (mm); E_a - Evaporation on i^{th} day(mm); W_{seep} –The quantity of water entering the vandose zone on i^{th} day (mm) and Q_{gw} - Qunatity of return flow on i^{th} day (mm).

SWAT-CUP is a process in which uncertainty analysis can be predicted through five different techniques.

3.3 Sufi-2 algorithm

In Sufi-2, much of the uncertainty due to parameters comes into account whether it may be related to conceptual models or measured data (Abbaspour et al. 2015). In this the inputs such as choosing of parameters, period of simulation which also includes warmup period, objective function etc., should be given much attention in order to get the best simulation output. The 95 PPU operates through Latin hypercube sampling which does not allow 5% of the bad simulations (Abbaspour et al. 2007). However, the strength of calibration of a model is determined by the two factors namely p and r-factors (Abbaspour et al. 2015; Arnold et al. 2012). After all the degree of uncertainty is determined by p-factor whose value ranges between 0 and 1. If the value of p-factor is 1 then it indicates 95 PPU band covers 100% of the measured data and lower value indicates high uncertainties (Setegn et al. 2009). The r-factor (Yang et al.2008) is much concerned about the consistency of the data thus describing the quality of model calibration. The lower value of r-factor is most reliable to have less uncertainty. Mostly a balance between both the factors gives satisfactory results. Sufi-2 also allows to use R^2 and NSE as objective function to get the well calibrated model. Moreover, the sensitivity of parameters can also be obtained through the Dotty plots which are as shown in Fig 4.a and 4.b. Finally, the new set of parameter ranges are obtained from this output calibration and validation of data.

The stepwise procedure followed in SUFI-2 as shown in figure.2

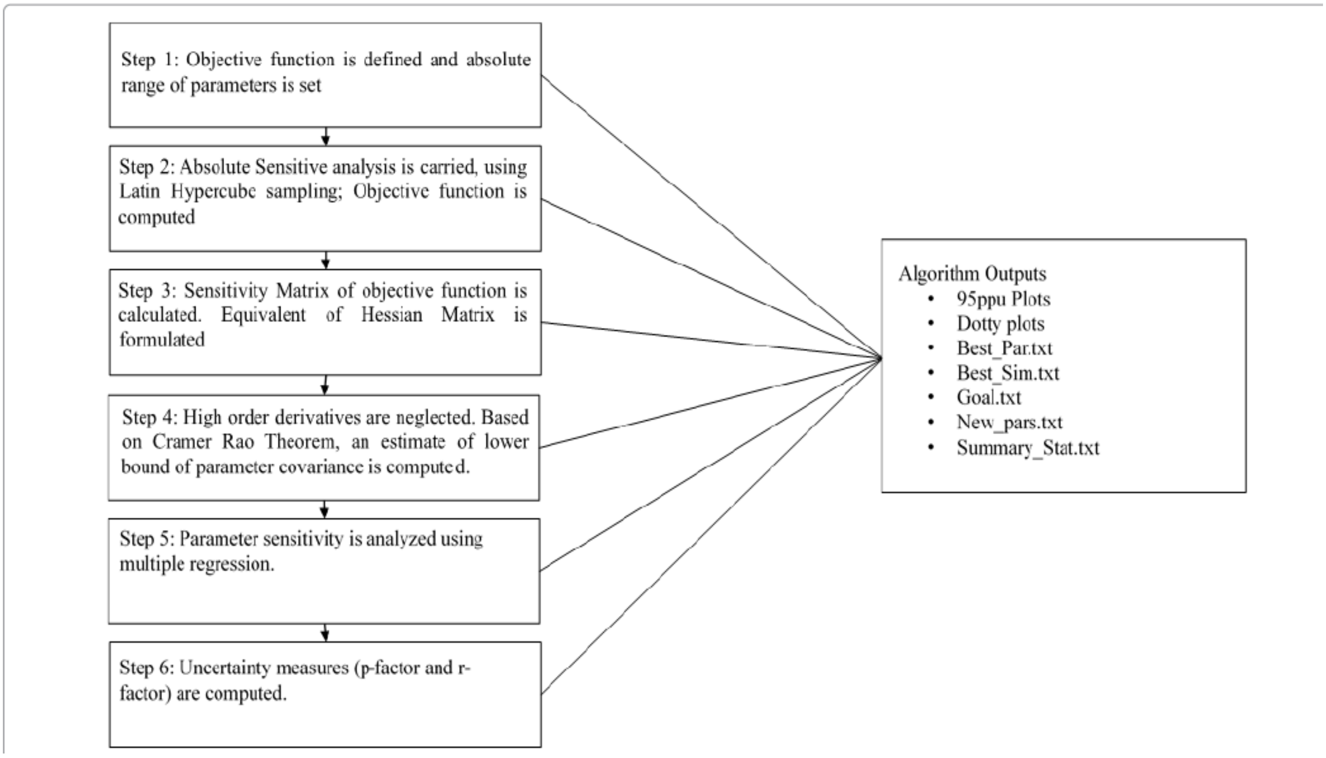

Figure 2. schematic representation of steps followed in SUFI-2 Algorithm (source: Hydrology current Research Article)

4.Results and Discussion

As we know the value of p and r factors decide the uncertainty. we also consider R^2 and NSE for better results.

$$r^2 = \frac{\left(\sum_{i=1}^{n}(O_i - \overline{O})(S_i - \overline{S})\right)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2 \sum_{i=1}^{n}(S_i - \overline{S})^2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(S_i - \overline{S})^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \qquad \text{r} - \text{factor} = \frac{\text{p} - \text{factor}}{\sigma_{\text{obs}}}$$

where O_i = observed value of data; O = mean observed value of data; S_i = simulated value of data; and S = mean simulated value of data

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4.1 Model set up

The total period of simulation was taken as 21 years (1987-2007) on the basis of monthly time step in SWAT CUP. Out of this, the model was calibrated for the period (1987-1999) (see Fig. 3a), considering first four years of datasets as warmup period (1987-1990) and the next 8 years were validated for the period (2000-2007) (see Fig. 3a). The calibrated streamflow was compared with observed streamflow values at Kursela gauge station which is taken closer to the outlet of Kosi basin. Sufi-2 algorithm was developed for the purpose of calibration and uncertainty assessment. A total of 10 parameters were chosen to simulate the streamflow with reference to earlier studies. The objective function was chosen to be NSE in order to get best simulation results. SWAT was used to divide the hydrologic model into small units and made it coupled with an interface called SWAT CUP. In this study minimum number of simulations produces the best and reliable output.

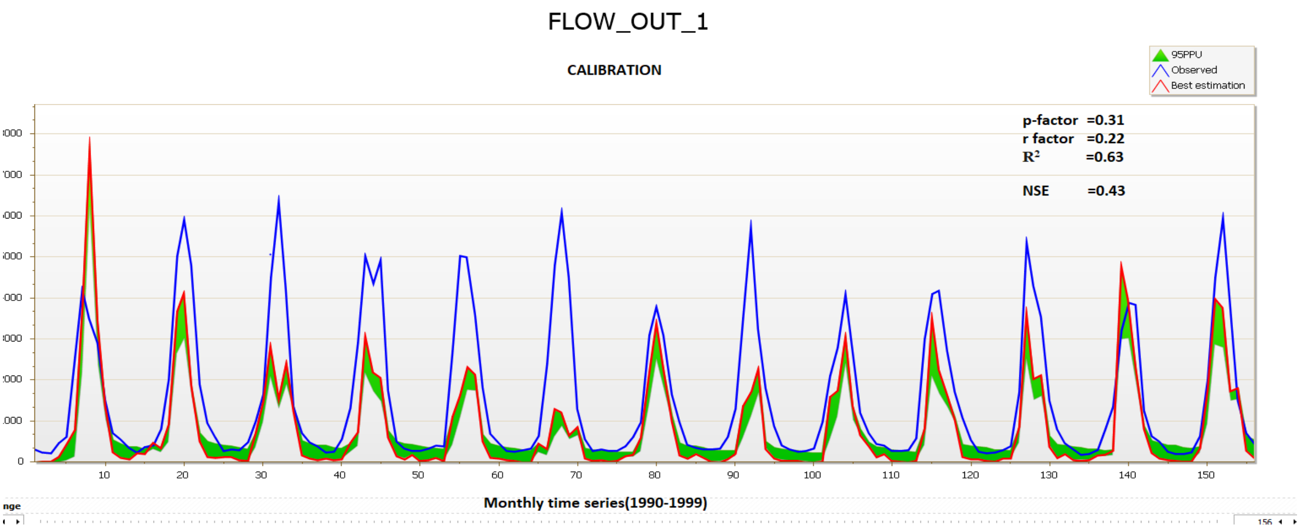

Figure 3a. 95 PPU plot of calibration for the period 1987-1999

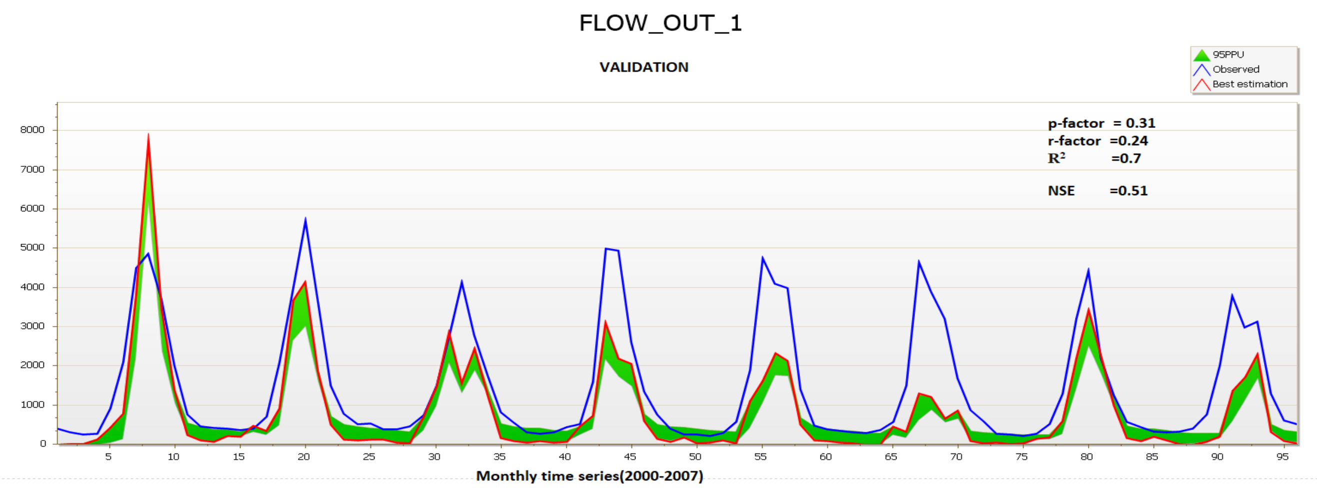

Figure 3b. 95 PPU plot of the validation for the period (2000-2007)

4.2 Model Calibration and Uncertainty Assessment

The 95 PPU plot obtained shows that the uncertainty assessment of streamflow of kosi basin. As the p-factor and r-factor obtained from the output plots are in balance though the 95PPU plot does not give satisfactory output which is because of the huge discharge variation of kosi basin seasonally. Dotty plots are which show the values of objective function as a function of parameters. In this study, they act as the indicators for the sensitivity of the parameters which are used for model calibration. The threshold value of objective function NSE is taken as 0.5. The results obtained are NSE<0.5 for calibration which indicate more uncertainty and for validation the value is satisfactory. The parameters taken in this study are shown in Table.2 along with their summary details. Out of the ten parameters, (r_ SFTMP .bsn, r__ SMTMP .bsn, r__ SMFMX .bsn) these three are snow parameters and the remaining are Land phase parameters.

S.NO	NAME OF THE PARAMETER	PARAMETER DEFINITION	NEW_MIN VALUE	NEW_MAX VALUE
1.	r __CN2.mgt	It is the SCS runoff curve number indicated with 'f'	-2.967	3.287
2.	v__ALPHA_BF.gw	It is the alpha factor for Base flow (days).	-32.972	34.772
3.	v__GW_DELAY.gw	It is the delay of Groundwater(days).	-111827.538	11971.538
4.	v__GWQMN.gw	It is the threshold depth of water required for return flow to occur in the shallow aquifer (mm).	-15.503	18.303
5.	r__ ESCO .bsn	It is the factor of compensation for Soil evaporation.	-2.292	2.492
6.	r__ EPCO. bsn	It is the factor of compensation for the Plant uptake.	-25.294	27.094
7.	r__GW_REVAP.gw	Coefficient of Groundwater "revap".	-1.103	1.179
8.	r__ SFTMP .bsn	Temperature of Snowfall.	-349.868	365.868
9.	r__ SMTMP .bsn	Temperature of the Snow melt base.	-363.073	331.073
10.	r__ SMFMX .bsn	It is the maximum melt rate for snow during the year.	-514.368	550.368

Table 2 summary table of parameter Ranges

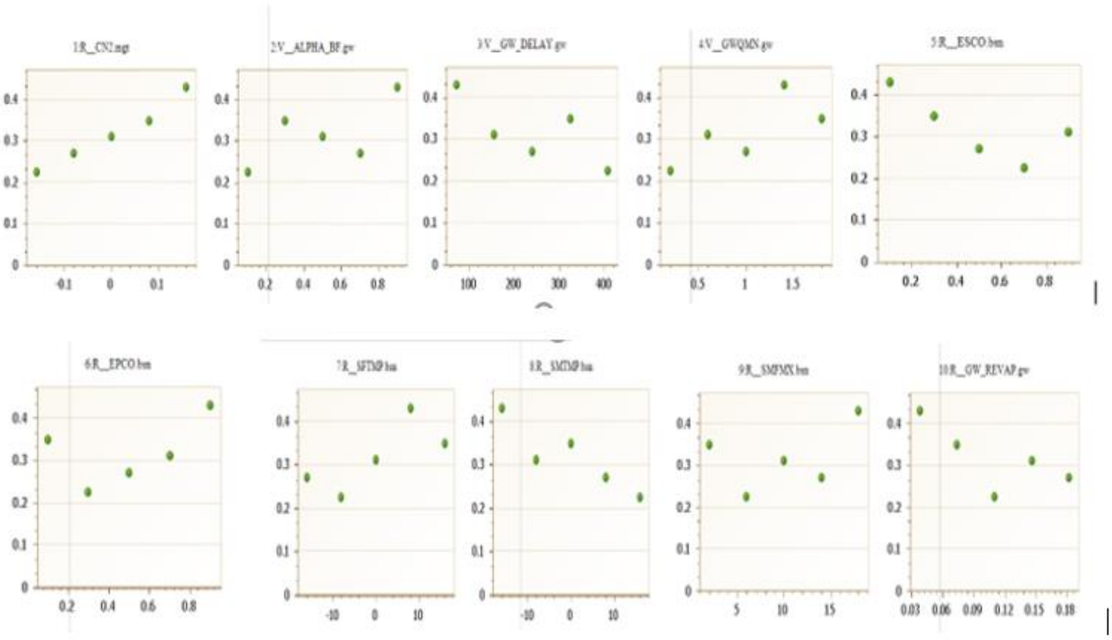

Figure 4.a Dotty plots of selected parameters with objective function NSE for calibration

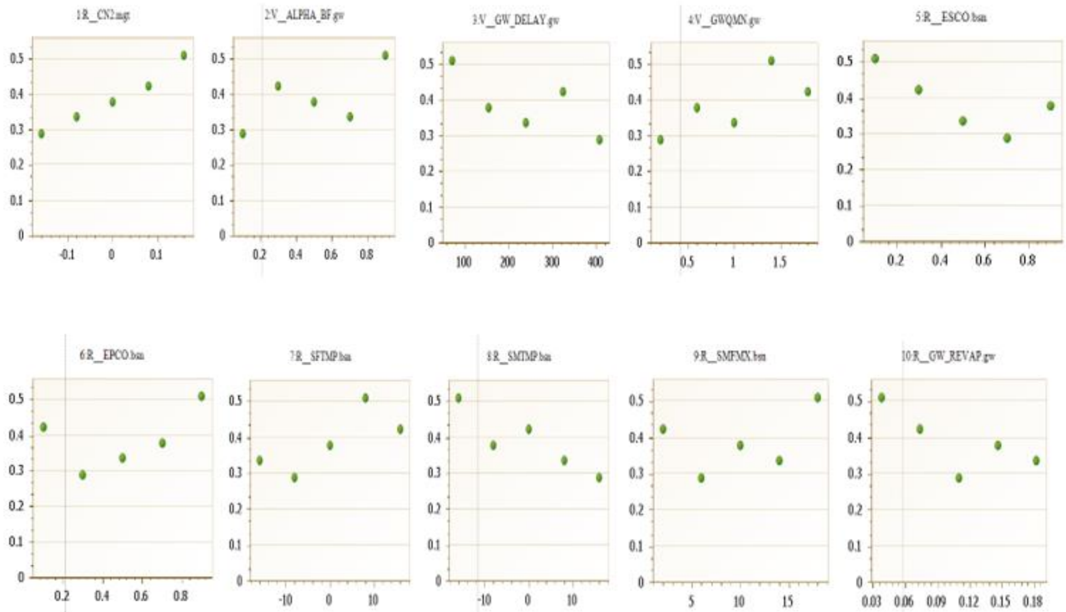

Figure 4.b Dotty plots of selected parameters with objective function NSE for validation

The results of calibration obtained revealed that parameter uncertainties were satisfactory only when the p and r-factors reach their desired range of values.While the factors like R^2 and NSE can ensure a goodness of fit between the observed data values and simulated output results. The extracted values of R^2 and NSE were 0.63 and 0.43 respectively for calibration and for validation, the values were 0.7 and 0.51 respectively which shows that the model was well calibrated for streamflow. In this study the main drawback is taking a single gauge station over such a large area. It is suggested to extend the number of stations and also to use the different types of uncertainty techniques to achieve the best simulation results for the sake of future studies.

5.Conclusion

To analyze the hydrologic response of parameters, a perfect calibration is required. In order to report the uncertainties, a model was setup in the kosi basin and calibrated from (1987-99) with first three years as warmup period. Now-a-days SUFI-2 became popular technique to estimate the uncertainties, so it was given priority in this study. The objective function was taken as NSE which produced a satisfactory result. The results from SWAT CUP indicate that this model is appropriate to predict the stream flow in kosi basin. The p and r factors obtained are not that satisfactory because SWAT is not able to simulate events at the level of extremities and it under estimates them. But R^2 and NSE values indicate the best simulation of streamflow in Kosi basin. Further studies can be done by using different techniques of uncertainty which can be used for the prediction of impact of climate change.

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