SindhUniv. Res. Jour. (Sci. Ser.) Vol. 53 (01) 59-66 (2021)

http://doi.org/10.26692/sujo/2021.03.10

SINDHUNIVERSITYRESEARCHJOURNAL(SCIENCE SERIES)

Calibrating and Validating the Soil Water Assessment tool on the NaiBaran Catchment

M. AHMED, G. H. DARS, H.U. ABBASI*

U.S-Pakistan Center for Advance Studies in Water Mehran University of Engineering and Technology Jamshoro

Received 24th October 2020 and Revised 16th January 2021

Abstract: Climate change is a major concern for water resource managers and planners. Water resources are under tremendous pressure affecting every aspect of life, especially hydrological cycles are vigorously affected. This research study focuses on calibrating and validating the Soil Water Assessment Tool (SWAT) on the NaiBaran Catchment. To calibrate and validate the model, meteorological data, land-use, digital elevation model, soil features, and observed flow data were used. For simulating the surface runoff from 2016 to 2019, the SWAT model was used while SWAT-CUP (Calibration and Uncertainty Program) was employed to calibrate and validate the model. The model performance was evaluated through statistical indices such as Nash-Sutcliffe efficiency co-efficient (NSE) and correlation coefficient (R^2); the results of these both indices were NSE 0.80; 0.92 and $R^2$0.81; 0.93 in calibrating and validating processes respectively. The results of these statistical indices showed that the SWAT model was successfully calibrated and validated on the NaiBaran catchment.

Keywords: Soil Water Assessment Tool, Calibration, Validation, Sensitivity Analysis, NaiBaran,

1. INTRODUCTION

Water resources are the most important constituent for the settlement of humans and their socio-economic development at the regional level; and are gaining more attention at the global scale due to their relationship with food security and energy (Wheeler and Von Braun, 2013, Carey *et al.,* 2014). It is predicted that water scarcity will increase at a global scale, especially in dense populous regions, and also climate variability, climatic conditions change towards the dry conditions and decreases in precipitation has been projected (Alcamo *et al.*, 2007, Burek *et al.*, 2016). Managing the water resources in these circumstances is a serious concern for water resource managers and policymakers. It is essential to analyze and quantify features of hydrologic cycles in a particular region. Most importantly the studies must be conducted at a catchment scale because of these hydrologic processes are taking place in that catchment. These hydrologic processes have been directly affected by meteorological conditions, topographical features, and land use of catchment, additionally the effect of anthropogenic activities (Ghoraba, 2015).

Hydrologic modeling plays a crucial role in monitoring and analyses of hydrological processes in a particular region or on a global scale, hydrologic modeling has a long history. However, it started in the 1850s when Mulvany designed the method to compute peak discharge and, it is still valid. With technological advancements, efficient hydrologic models have evolved with time; presently, there are several hydrologic models are being used by researchers all around the globe for numerous purposes such as flood risk assessment, water resource management, monitoring water quality, and surface runoff analysis (Singh, 2018, Stephens *et al.,* 2019).

Soil Water Assessment Tool (SWAT) (Arnold and Williams, 1987) is emerged as efficient hydrologic model to monitor and analyze the hydrological processes and it is worldwide used by researchers from a basin scale to a catchment. (Arnold and Allen, 1996) successfully calibrated and validated the SWAT model on three watersheds in Illinois Texas by monitoring surface flow groundwater flow, and evapotranspiration. (Santhi *et al.*, 2001) applied the SWAT model on a watershed in Texas and reported the successful validation of several water balance elements another study conducted by (Arnold *et al.,* 1999) using the SWAT model in which they employed large amount of data for validation of surface runoff of watershed in Texas and they reported the successful validation of model. The SWAT model was used in Northern Mississippi by (Bingner, 1996) for validating the stream flow of several sub-basins and reported the successful validation of model another study conducted by (Setegn *et al.*, 2008) using the SWAT model on Lake Tana balance to predict hydrologic water balance and reported the successful calibration and validation of model and there other numerous research studies

Emails: jiskanimansoorahmed@gmail.com , ghdars.uspcasw@faculty.muet.edu.pk, habibullah.abbasi@usindh.edu.pk
*Centre for Environmental Science, University of Sindh Jamshoro.

which reported the successful calibration and validation of the SWAT model all around the globe such as (Pandey *et al.*, 2019, Garee *et al.*, 2017, Wang *et al.*, 2008).

The aim of this study was to calibrated and validate the SWAT model on NaiBaran catchment by using SWAT-CUP (SWAT Calibration and Uncertainty Program).

Study Area

NaiBaran is located near to Janghri village 20 km away from the Karachi-Hyderabad motorway (M9), 70 km from Hyderabad, and 135 km from Karachi. The NaiBaran is located in an arid, and the desert consists of sedimentary rocks. Hill torrents are spread over 3150 km^2 in the lower Khirthar National Park ranges, those are the maintributaries of supplying water to NaiBaran. The topographical features of the upper catchment consist of sub-mountainous to rocky and plain (Begum *et al.*, 2013).

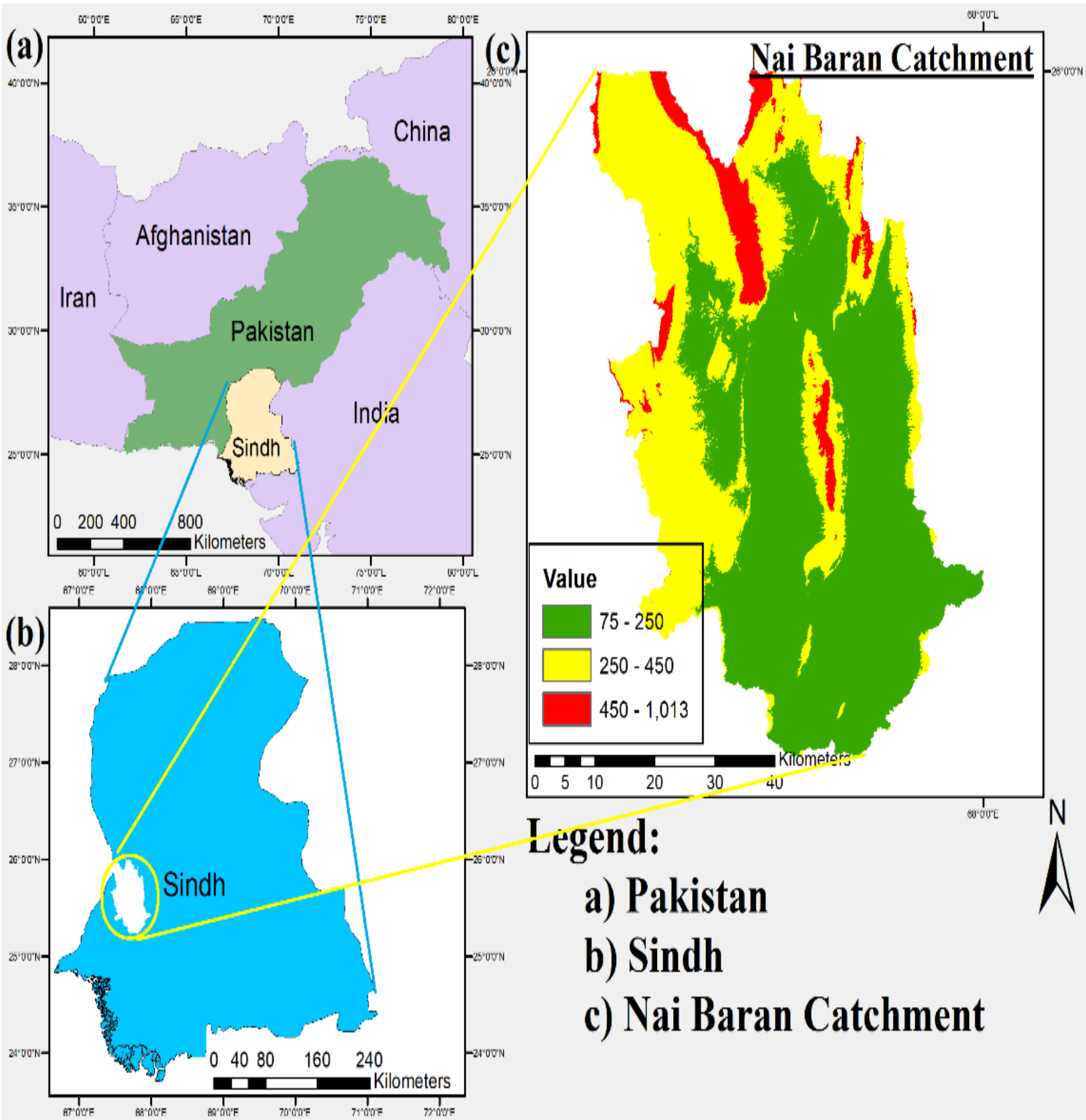

Fig.1. Study area

2. MATERIALS AND METHODS

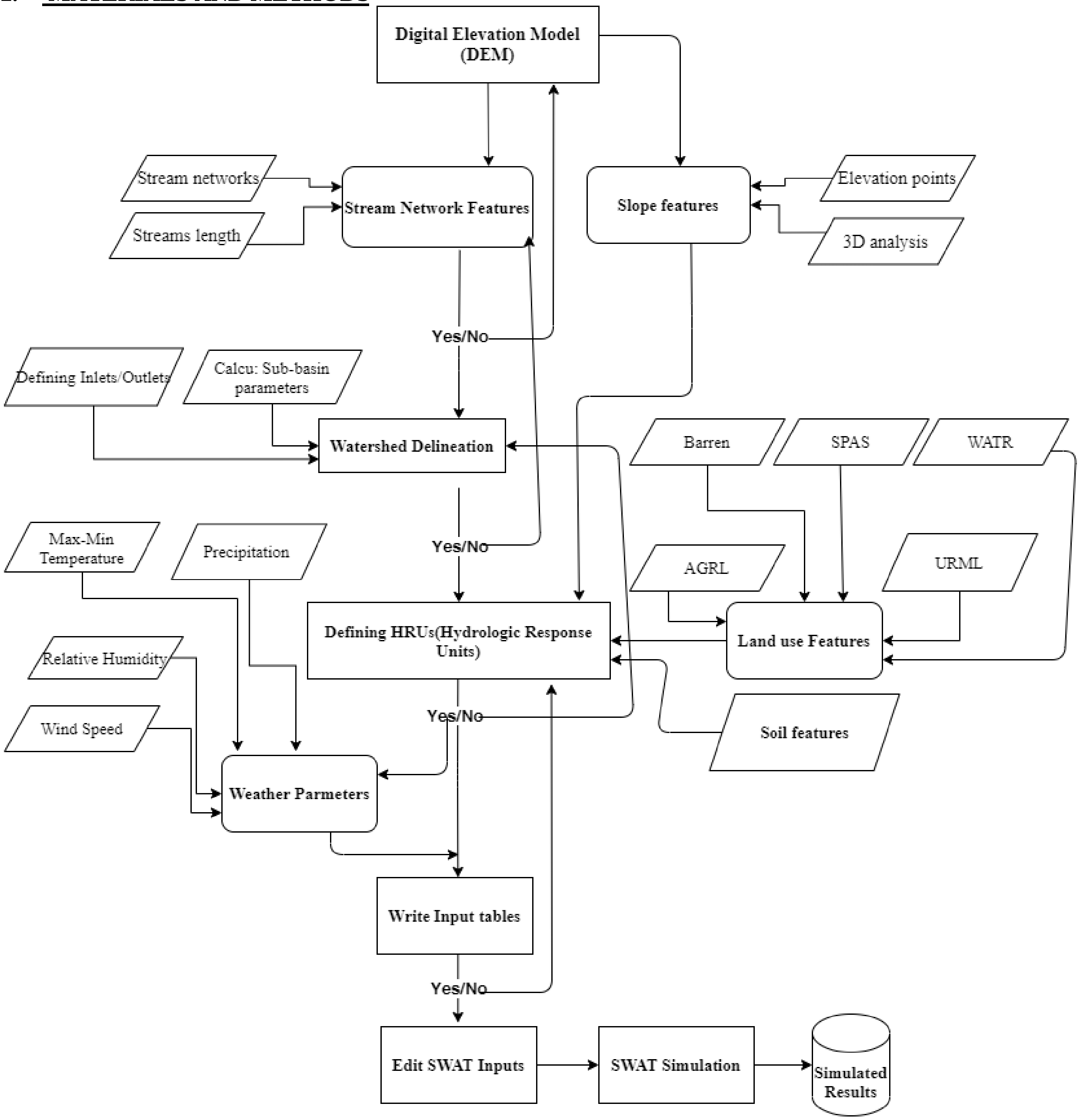

Fig. 1 Methodological framework of research study

Soil Water Assessment Tool (SWAT)

Soil Water Assessment Tool (SWAT) (Arnold and Williams, 1987) is a basin-scale model based on physical projections, which was developed to resolve the limitations in modeling. This tool is comprised of daily time scale projections, high-level spatial description, numerous subdivisions of the watershed, effective analysis. In addition, it is capable of simulating the variations in land management. SWAT's various applications are tested in terms of monitoring flow and pollutant deposits comparing with observed data on numerous watersheds (Arnold *et al.,* 1999, Arnold *et al.,* 1998, Saleh *et al.,* 2000). SWAT is successfully used to monitor the hydrologic response of various river basins with climate change such as the Upper Mississippi River Basin and Missouri River Basin (Jha *et al.,* 2004, Stone *et al.,* 2001). Assessing the point and non-point source pollutants in a basin, the SWAT model is implied worldwide and also selected by the Environmental Protection Agency for monitoring the watersheds (Whittemore, 1998). Along with the successful implications of physical-based models, some limitations question the model outputs like uncertainty in input factors, nonlinear relation with hydrologic input factors and hydrologic response, and calibration for various model factors. For that purpose, sensitivity analysis is important to analyze the sensible parameters. It can help examine the projected results and minimize uncertainty (Lenhart *et al.*, 2002). It uses the HRUs which contain information about land-use, soil, and slope properties. The HRUs define the region's variability on the bases of land-use, type of soil, and slope classes in a catchment. The SWAT model calculates the related hydrological factors like evapotranspiration, surface flow, and peak rate of flow, subsurface flow, and rate of sediment deposit for every HRUs.

SWAT extension is connected with ArcGis, which is employed as a graphical user interface for SWAT2012. This is extended from an earlier version of AVSWAT, which was embedded in ArcView. The hydrological process in SWAT is projected by using the water balance equation.

$$SW_t = SW_0 + \sum_{i=0}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{qw}\right) \quad (1)$$

Where SW_t represents the total soil water content (mm), SW_0 represents the initial soil water content in a day i (mm), t represents the time (day), R_{day} represents the total amount of rainfall in a day i (mm), Q_{surf} represents the total amount of surface flow in a day i (mm), E_a represents the total evapotranspiration in a day i (mm), W_{seep} represents the total amount of water entered in the vadose zone in a day i (mm), and Q_{gw} represents the total amount of return flow in a day i (mm). There are two methods to calculate the surface runoff which is the SCS curve number developed by USDA Soil Conservation Service and the Green and Ampt infiltration technique (Green and Ampt, 1911).

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

Q_{surf} represents the total accumulated flow/ precipitation surplus (mm), R_{day} represents the amount of precipitation depth in a day (mm), where is S for the retention factor (mm), which is calculated by following equation:

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

Soil's permeability, land-use, and precursor soil water circumstances are defined by the SCS curve number function. SCS classify precursor moisture circumstances into three categories: one dry, second average moisture, and third wet.

Data Sets

Simulating the water balance of any area requires, the data categorized into two groups, static data and dynamic data. Static data consists of DEM, Soil, Land use, and dynamic data consist of weather data that includes maximum and minimum temperature, precipitation, relative humidity, and wind speed, and also observed flow data is required.

Table. 1. Data used and sources

Data Type	Description	Data source
Digital Elevation Model	DEM with a resolution of 90x90 meter	(NASA, USGS)
Soil	Soil features/characteristics	(FAO, UN)
Land use	Land use classes	(U.S. Geological Surve, 2016)
Weather data	Daily weather variables data (2012 - 2019)	(CFSR)
Flow data	Daily observed flow data	(WAPDA)

Digital Elevation Model (DEM)

Topographical features are defined by a DEM, which provides elevation values for any point in a particular region with a specific spatial resolution. The DEM with a resolution of 90x90 meter Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) was downloaded from (USGS, 2016). ArcSWAT uses the DEM for watershed delineation and evaluates the drainage patterns of land cover topography. DEM is also used for defining the Sub-basin components such as slope, terrain's slope length, and stream network features.

Soil Data

Soil's various features, such as soil texture and physicochemical properties, are required as input in the SWAT model. The soil data was acquired from FAO Soil maps (FAO, 2005). This data was processed and extracted for the NaiBaran catchment by using the ArcGIS.

Land Use

TheLandsat-8 satellite data was used in this research which orbits at 705 km altitude. The multi-spectral satellite data was downloaded from(U.S. Geological Surve, 2016).The data was mosaic to clip the study area for further classification. Supervised classification Maximum Likelihood Classifier was implemented to classify land use / cover classes into water bodies, natural vegetation, agricultural areas, barren land, and residential areas by using ArcGIS software.

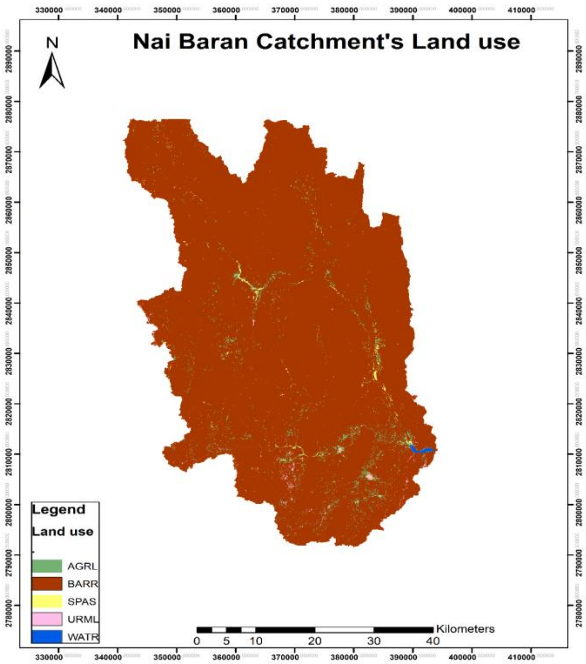

Fig. 2 Land use map of NaiBaran Catchment

Weather Data

Weather data is an important input parameter in the SWAT model. This can directly be read from observed data or can be generated through the weather generator model available in the SWAT model. Various weather variables were utilized to drive the hydrological balance, such as daily rainfall, minimum and maximum temperature, humidity, and wind speed. The data was acquired from 2012 to 2019 in accordance with the availability of observed flow data.

Flow Data

For calibrating and validating the SWAT model, observed flow data was acquired from WAPDA (WAPDA, 2014) for the four years from 2016 to 2019. Two years of data, i.e., 2016 through 2017, was used for calibration, and two years of data, i.e., 2018 through 2019, was used for validation.

Setting up Model Run

SWAT model was used to project the all water balance components of the study area. In the simulation process, the first step is to delineate the watershed, which was done using ArcGis. The ASTER DEM was used to delineate the watershed, which was downloaded from (USGS, 2016). The second step in the ArcSWAT (interface for SWAT in ArcGis) is to define the HRUs. HRUs are divided on the bases of land use, soil, and slope with similar characteristics. HRUs are important to determine the water balance of water as it is reported by (Arnold *et al.*, 2012, Neitsch *et al.*, 2011) that similar HRUs would have similar hydrological features. The third step is to give input data (maximum and minimum temperature, precipitation, relative humidity, and wind speed). The weather generator tool in the ArcSWAT was enabled to fill any missing data of the stations. The weather generator tool contains the long-term simulated data of maximum and minimum temperature, precipitation, relative humidity and wind speed (Neitsch *et al.*, 2011). After the completion of all necessary steps SWAT simulation was started, the simulation period was set from 2012 to 2019 and four years were set to be the warming period (2012 through 2015).

Calibration, Validation and Sensitivity analysis of Model

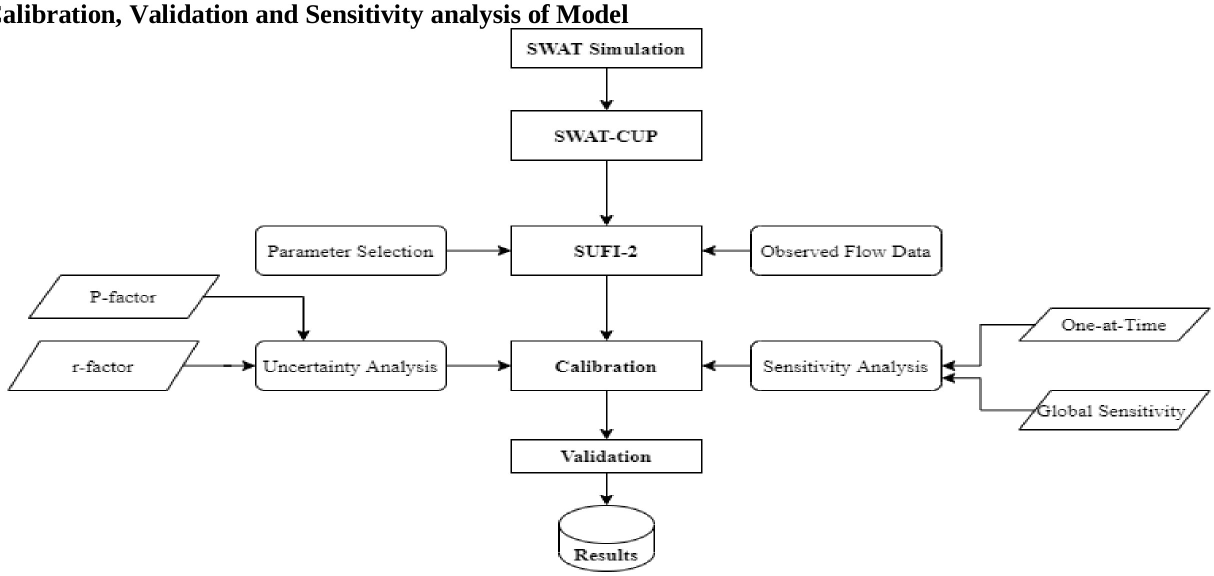

Fig. 3 Methodological framework for calibration and validation

The success of the hydrological model is very much rely some important processes suchas calibration, validation, and analyzing of sensitivity ofparameters (Abbaspour, 2015, Kouchi *et al.,* 2017). In this research study SWAT-CUP has been implemented by employing the SUFI-2 algorithms in the process of sensitivity analysis, calibrating and validating the model. However information about the SUFI-2 algorithm is given in the manuscripts and tutorials(Abbaspour, 2015; Abbaspour *et al.,* 2007). This technique was implemented for the selection of sensitive parameters by selecting the one parameter at a time (OAT) option. More parameters has been selected by implementing the global sensitivity tool. The whole process was achieved by compiling the SUFI-2 iteration with five hundred simulations. It is reported by (Abbaspour, 2015, Blöschl *et al.,* 2013)that model uncertainties can occur due to various components such as weather variables, during model setup, observed datasets, or uncertainty may occurduring parameterization process. Uncertainties due to parameters and model outputs are expressed as the 95% probability division, with the use of the Latin Hypercube Sampling. However SWAT-CUP measured uncertainty sources in-terms p-factor and r-factor where p-factor is used for representing the percentage of measured data and on other hand r-factor is the thickness of enveloped by r-factor also known as 95PPU. For evaluating the model performance SUFI-2 has wide range of options which can also be implemented for evaluation of model accuracy, those are R^2, and NSE these indices were used in this research study during the model calibrating and validating processes.

$$NSE = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2} \qquad (4)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n} (Q_{m,i} - \bar{Q}_m)(Q_{s,i} - \bar{Q}_s)\right]^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2 \sum_i (Q_{s,i} - \bar{Q}_s)^2} \qquad (5)$$

Where Q_m represents the measured flow, and Q_s represents the simulated flow; whereas $\bar{Q}_m$ represent the average of measured flow and $\bar{Q}_s$ represents the average of simulated flow and $i$representsi^{th} measured or simulated data.

3. RESULTS AND DISCUSSION

Sensitivity Analysis

Multiple model parameters, which have high sensitivity value, have been utilizedin the model calibrating and validating processes. The list for those sensitive parameters is provided in the table below.

Table 2. List of parameters selected in calibration and validation processes

Parameter Name	t-Stat	P-Value	Min: Value	Max: Value	Fitted Value	Description
R__CN2.mgt	23.657	0.00000	-0.3	0.150	0.030500	SCS runoff curve number factor
V__ALPHA_BF.gw	0.71959006	0.47215	0.00	0.200	0.0104	Base flow alpha factor (days)
R__SLSUBBSN. hru	-0.0920185	0.92672	-0.2	0.2	-0.179	Average slope length.
V__GW_DELAY.gw	-0.5020215	0.61590	0.0	100.0	14.55	Groundwater delay (days)
R__SOL_K (...).sol	-0.7784921	0.43669	-0.8	0.8	0.286	Saturated hydraulic conductivity
V__RCHRG_DP.gw	-1.4792148	0.13979	0.0	0.5	0.103	Deep aquifer percolation fraction.
R__SOL_AWC (...).sol	-1.531150	0.12644	0.0	0.5	0.0827	Available water capacity of the soil layer
R__SOL_BD (...).sol	-5.5046200	0.00000	-0.3	0.3	0.2726	Moist bulk density

Table 2 shows a list of parameters used in calibration and validation processes. The table provides the parameter name, t-stat, P-value, minimum, maximum ranges, fitted values, and parameter description, while t-stat represents the sensitivity of parameters higher the t-stat, higher the parameter's sensitivity, and P-value shows the optimum number of iterations have been used to analyze the sensitivity of parameters, so P-value should be equal to zero or nearer to zero. Although parameters minimum and maximum ranges have been set for successful calibration and validation processes, and parameters fitted values have been shown show in **(Table 4).**

Calibration and Validation

The graph consists of observed flow and simulated flow for the watershed are shown in the **(Fig. 4 and 5)** for calibration and validation period, respectively.

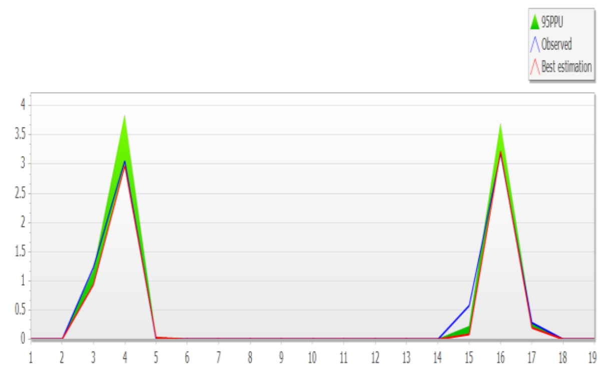

Fig. 4 Calibration graph, calibrated on monthly time scale (2016-2017)

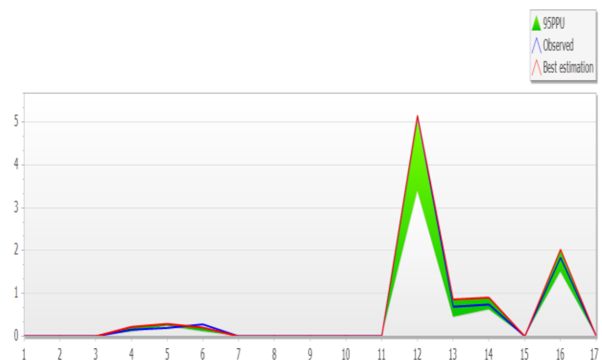

Fig. 5 Validation graph, validate on monthly time scale (2018-2019)

Table 3. Statistical indices values acquired in calibration and validation processes

Process	NSE	R^2
Calibration	0.80	0.81
Validation	0.92	0.93

The model performance indicators and their acquired results are shown in Table 3. The NSE, coefficient of determination (R^2).(Abbaspour, 2015, N. Moriasi *et al.*, 2007) stressed to keep the model performance indicators ranges (R^2 and NSE > 0.71), hence, the value of NSE 0.80, 0.92; the value R^2 0.81, 0.93, for calibration and validation processes respectively have been achieved. So in our research study, the statistical indices show that model simulated flow and observed flow are in a good connection.

CONCLUSION

By implementing land use, soil features, DEM and weather parameters, the SWAT model was successfully applied on the NaiBaran catchment by using the SWAT-CUP. Sensitivity analysis was performed by using the One-at-time, global sensitivity techniques and parameters uncertainty was analyzed in-terms of P-factor and r-factor. The model was calibrated from 2016 to 2017 and validated from 2018 to 2019 on the monthly time scale. For achieving the optimum results in calibration and validation processes, the land use map was generated by using maximum likelihood classifier which resulted 0.98 kappa coefficient. On other hand soil features were also adjusted according to the soil profile of the study area. However using DEM,3D analysis was performed for defining the slopes and for generating the slopes in HRUs definition process. Multiple statistical indices such as NSE, and R^2were used for model calibration and validation processes. The value of NSE for both calibration and validation were estimated to be 0.80 and 0.92 respectively. The value of R^2 for both calibration and validation were estimated to be 0.81 and 0.93 respectively.

The results showed that the SWAT model performed well on the NaiBaran catchment for projecting the surface runoff and can also be used for analyzing the likely future impacts of climate change on the hydrological cycles of the study area.

This scientific research study will be helpful for water managers and policy makers to draw the road map for conserving and managing the water resources with consultation to all the stakeholders for sustainable water resource management.

REFERENCES:

Abbaspour, and C. Karim (2015). SWAT-CUP: SWAT Calibration and Uncertainty Programs - A User Manual. *EAWAG: Swiss Federal Institue of Aquatic Science and Technology***,** 1-100.

Alcamo, J., F. Martina and M. Michael (2007). Future long-term changes in global water resources driven by socio-economic and climatic changes. *Hydrological Sciences Journal*, 52**,** 247-275.

Arnold, J. G. and P. M. Allen, (1996). Estimating hydrologic budgets for three Illinois watersheds. *Journal of Hydrology*, 176**,** 57-77.

Arnold, J. G., R. Srinivasan, R.S. Muttiah, and P.M. Allen, (1999). Continental Scale Simulation Of The Hydrologic Balance1. *Jawra Journal of the American Water Resources Association*, 35**,** 1037-1051.

Arnold, J. G. and J. R. Williams, (1987). Validation of SWRRB—Simulator for Water Resources in Rural Basins. *Journal of Water Resources Planning and Management*, 113**,** 243-256.

Arnold, J. G., M. Daniel, N. Gassman, W. Philip C. White, J. Michael, S. Raghavan, S. Chinnasamy, R.D. Harmel, V.G., Ann and V. W. Michael (2012). SWAT: Model use, calibration, and validation. *Transactions of the ASABE*, 55**,** 1491-1508.

Arnold, J. G., S., M. Raghavan, S. Ranjan and W. Jimmy (1998). Large area hydrologic modeling and assessment part I: model development 1. *JAWRA Journal of the American Water Resources Association,* 34**,** 73-89.

Begum, A., G. S. Ali, Z. A. Khan, and T. Fozia (2013). A Qualitative Study of the Wildlife of Darawat Dam, Thatta district, Sindh, Pakistan. *International Journal of Advanced Research,* 1**,** 202-206.

Bingner, R.L. (1996). Runoff simulated from Goodwin Creek watershed using SWAT. *Transactions of the ASAE,* 39**,** 85-90.

Blöschl, G., S. Murugesu and V. Alberto (2013). *Runoff prediction in ungauged basins: synthesis across processes, places and scales*, Cambridge Univ. Press.

Burek, P., Y. Satoh, G. Fischer, S. Eisner, and M. Flörke, (2016). Water futures and solution: fast track initiative (final report). *IIASA, Laxenburg, Austria*.

Carey, M., B. Michel, M. Bryan. and McKenzie, M. Jeffrey (2014). Toward hydro-social modeling: Merging human variables and the social sciences with climate-glacier runoff models (Santa River, Peru). *Journal of Hydrology,* 518**,** 60-70.

FAO. (2005). *FAO-UNESCO Soil Map of the World, at 1:5.000.000 scale.* [Online]. Available: http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/ [Accessed 1-05-2019].

Garee, K., Chen, Xi, B. Anming, and M. Fanhao (2017). Hydrological modeling of the upper indus basin: A case study from a high-altitude glacierized catchment Hunza. *Water,* 9**,** 17.

Ghoraba, S. M. (2015). Hydrological modeling of the Simly Dam watershed (Pakistan) using GIS and SWAT model. *Alexandria Engineering Journal,* 54**,** 583-594.

Green, W H. and G.A. Ampt, (1911). Studies on Soil Phyics. *The Journal of Agricultural Science,* 4**,** 1-24.

Jha, M. P., Z. Takle, and G. Roy (2004). Impacts of climate change on streamflow in the Upper Mississippi River Basin: A regional climate model perspective. *Journal of Geophysical Research: Atmospheres,* 109Pp.

Kouchi, D. H., E. Kazem, S. Hossein, K. Davar and A. Karim (2017). Sensitivity of calibrated parameters and water resource estimates on different objective functions and optimization algorithms. *Water,* 9**,** 384Pp.

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

Neitsch, S., L. Arnold, G.Jeffrey and W. Jimmy (2011). Soil and water assessment tool theoretical documentation version 2009. Texas Water Resources.

Pandey, V. P., D. Sanita, B. Luna and T. B. Raj (2019). Hydrological response of Chamelia watershed in Mahakali Basin to climate change. *Science of the Total Environment,* 650**,** 365-383.

Saleh, A, J.G. Arnold, P.W. Gassman, and McFarland, (2000). Application of SWAT for the upper North Bosque River watershed. *Transactions of the ASAE,* 43**,** 1077Pp.

Santhi, C., A. Jeffrey, G. W. Jimmy R. D. William, A. Srinivasan, and H. Larry M (2001). Validation of the swat model on a large rwer basin with point and nonpoint sources 1. *JAWRA Journal of the American Water Resources Association,* 37**,** 1169-1188.

Setegn, S. G., R. Srinivasan, and B. Dargahi, (2008). Hydrological modelling in the Lake Tana Basin, Ethiopia Using SWAT Model. Open Hydrol J 2: 49–62.

Singh, V. P (2018). Hydrologic modeling: progress and future directions. *Geoscience Letters,* 5**,** 1-18.

Stephens, C. M., L. A. Marshall, and F. M. Johnson, (2019). Investigating strategies to improve hydrologic model performance in a changing climate. *Journal of Hydrology,* 579**,** 124219.

Stone, M. C., H. Rollin H. Hubbard, and A. Jeff (2001). Impacts Of Climate Change On Missouri Rwer Basin Water Yield 1. *JAWRA Journal of the American Water Resources Association,* 37**,** 1119-1129.

USGS. (2016). *U.S Gelogical Survey* [Online]. USGS. [Accessed 25-08 2019].

Wang, S. K., S. Zhang, and L Fusheng (2008). Modelling hydrological response to different land-use and climate change scenarios in the Zamu River basin of northwest China. *Hydrological Processes: An International Journal,* 22**,** 2502-2510.

WAPDA. (2014). *Darwat Dam Project* [Online]. WAPDA Water Wing. [Accessed].

Wheeler, T. and V. R. Joachim (2013). Climate change impacts on global food security. *Science,* 341**,** 508-513.

Whittemore, R. C. (1998). The BASINS model. *Water environment and technology,* 10**,** 57-61.