Plant Archives **Vol. 25, Special Issue (ICTPAIRS-JAU, Junagadh) Jan. 2025 pp. 297-305**
e-ISSN:2581-6063 (online), ISSN:0972-5210

Plant Archives

Journal homepage: http://www.plantarchives.org
DOI Url : https://doi.org/10.51470/PLANTARCHIVES.2025.v25.SP.ICTPAIRS-045

MODELLING STREAMFLOW IN MACHHUNDRI RIVER BASIN WITH SWAT AND ANN APPROACHES

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ABSTRACT

Accurately estimating surface runoff is crucial for effective water resource planning and management. Streamflow estimation, as a key non-structural flood management measure, provides critical advanced knowledge of potential flooding events. The integration of remote sensing data and GIS with spatially distributed hydrological models offers substantial potential for simulating hydrological processes, such as streamflow, within watersheds. Data-driven models, which are characterized by their minimal data requirements and ease of development, have demonstrated high accuracy in hydrologic prediction applications. In the study, Soil and Water Assessment Tool (SWAT) and Artificial Neural Network (ANN) were applied to simulate the streamflow in Machhundri river basin located in Gir Sanctuary of Saurashtra region of Gujarat, India. The catchment area was determined to be 209.65 km^2, with a perimeter of 108.16 km. In the study, sixteen years of climatic and discharge data were divided into calibration period of thirteen years data and validation period of three years data. The climatic and discharge data, DEM imagery, soil maps and land use/cover classification from IRS P6 of sensor LISS III imagery were used as primary inputs for SWAT model, whereas only climatic and streamflow data were used for ANN model setup. Auto-calibration of the SWAT model was carried out using the ParaSol optimization method in SWAT-CUP software and calibrated values of the sensitive parameters were obtained. Final simulated streamflow statistics of SWAT model for the Machhundri watershed were NSE=57.88 %, R^2 = 0.68 and NSE = 65.54 %, R^2 = 0.83 for calibration and validation periods respectively. ANN model with Levenberg Marquardt algorithm and inputs as 1 day lag of rainfall and streamflow (2-12-1) performed best with R^2, RMSE and NSE values of 0.965, 1.88 cumec and 96.46 % for calibration and 0.94, 1.94 cumec and 94.34 % for testing period. ANN was better at simulating peak flows in Machhundri watershed.

***Key words*: Streamflow estimation, SWAT, ANN, Hydrologic modelling**

Introduction

Watershed hydrology is of central importance to the structure and function of stream ecosystems. Streamflow, which is known an integrated process of atmospheric and topographic processes, is of prime importance to water resources planning (Kahya and Dracup, 1993). Stochastic by nature, streamflow varies over time in response to precipitation and is inherently subjected to episodic extremes of high and low flows. Streamflow also varies among watersheds due to complex physiographic, landscape, and disturbance characteristics. Given the great importance of hydrology to stream ecosystems, accurate prediction or forecasting of streamflow is of utmost importance.

Generally, river runoff prediction models are classified into physical and data-driven based methodology. The first approach has complex structure and it needs rather deep mathematical knowledge. In the actual applications, researchers often apply these models in water resource modelling, especially runoff of rivers. A good runoff model includes spatially variable parameters such as rainfall, soil types and land use/land cover etc. (Kumar *et al.*, 1997).

The Soil and Water Assessment Tool (SWAT) is one of the most widely used and renowned models developed jointly by the United States Department of Agriculture (USDA), Agricultural Service and Agricultural Experiment Station in Temple, Texas. It is a physically based, continuous time, long-term simulation, lumped parameter, deterministic, and originated from agricultural models. In India, researchers also used the SWAT model to conduct hydrologic studies under climate change conditions (Oo *et al.*, 2020; Li and Fang, 2021), sub-watershed prioritization and management perspective analysis (Mishra *et al.,* 2007; Wu *et al*., 2023), and regional hydrology for the assessment of water resource potential (Swain *et al*., 2023). In spite of several advantages of physically based models, they require intensive data and solution of complicated differential equations for their implementation. In addition, several spatial and temporal data are required to calibrate the conceptual/physical based models and difficulty arises in the application of these models when only limited data are available to make forecasts.

Data driven models can be calibrated using short length of time series data with or without exhaustive temporal and spatially distributed information as required by physically based models. The performance of these models is found to be very promising and applied widely because of the ease in their development and potential to be used in real field conditions. Regression models and neural networks (NNs) are the most popular data driven models. However, NNs are found to be more accurate than regression methods (Sahay and Sehgal, 2013). The water resources applications using ANNs include the simulation rainfall runoff event, climate change, evapotranspiration process, river ûow forecasting, reservoir inûow modelling, ground water quality prediction, etc. (Chakravarti *et al.*, 2015).

The study area, Machhundri reservoir, comes under Una taluka of Gir Somnath district located in Gujarat state of India. Machhundri project lies in the basin of Shetrunji and other east flowing rivers. It was imperative to know how physical based model and an artificial neural network perform in predicting the streamflow while having limited data availability. Therefore, the study was intended to explore detailed knowledge and analysis of rainfall and runoff relationship to enhance the management of water, planning and to predict streamflow to mitigate the negative effects of floods and droughts in Machhundri reservoir.

Material and Methods

The catchment area of Machhundri reservoir is 210 km^2. Most of this catchment area falls under Gir Gadhda taluka of Gir Somnath district, while a small remaining portion is under Dhari taluka of Amreli district. Machhundri irrigation scheme has 9995 ha gross command area, which benefits 21 villages. The location of Machhundri watershed is shown in Fig. 1, where the locations of gauging stations for climate, rainfall and inflow data are also shown. As the area falls under Gir National Park, the weather data availability was very limited.

The remote sensing data *i.e.* digital elevation model (DEM), soil map and land use/land cover map were obtained from Bhaskaracharya Institute for Space

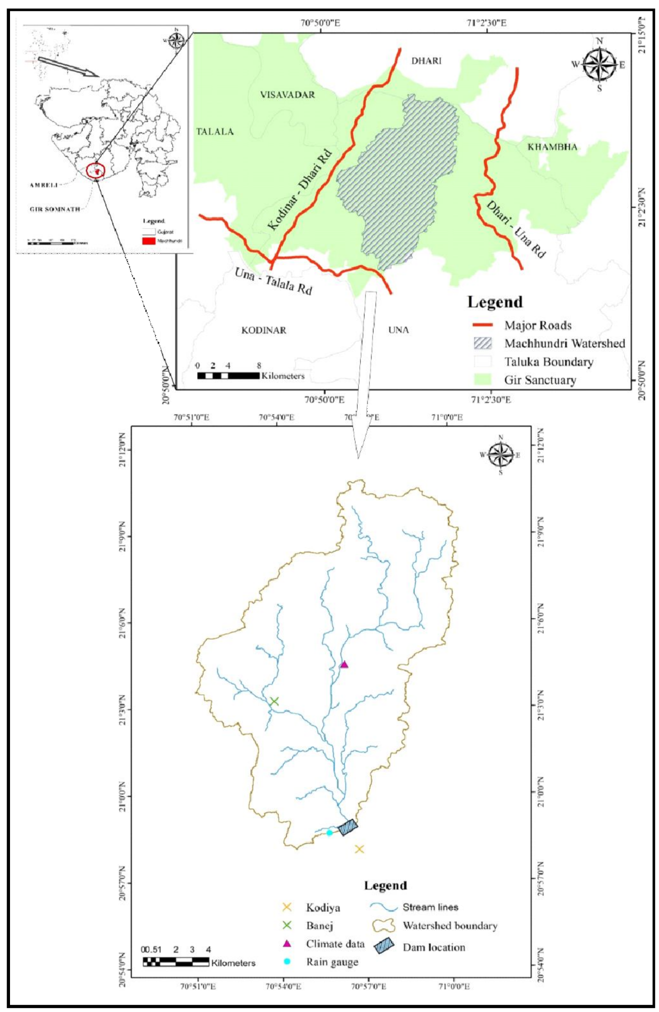

Fig. 1: Location map of Machhundri watershed.

Table 1: Description of hydro meteorological and remote sensing data with their sources.

Sr. No.	Data	Description	Source
1	Hydrological and Meteorological Data	Daily rainfall (2000-2015) Daily stream flow (2000-2015)	Junagadh Irrigation Division, NWRWS, Junagadh
		Daily max and min temperature (2000-2015) Daily relative humidity (2000-2015) Daily average wind speed (2000-2015) Daily solar radiation (2000-2015)	State Water Data Center, Gandhinagar and Global Weather database Bhaskaracharya Institute for Space
2	Remote Sensing Data	Land use/land cover map (2011-12) Soil map (2005) DEM (2011)	Applications and Geoinformatics (BISAG), Gandhinagar

Applications and Geoinformatics (BISAG), Gandhinagar. The DEM file was obtained from BISAG, which was generated using Indian Remote Sensing Satellite Cartosat-1 of year 2011. Land use/land cover map acquired was prepared from remote sensing image data of IRS P6 from LISS-III sensor of year 2011-12. Soil map obtained was prepared by National Bureau of Soil Survey and Land Use Planning (NBSS & LUP). Daily rainfall and daily stream flow data of 16 years (2000-2015) of Machhundri reservoir were obtained from Junagadh Irrigation Division, Junagadh. Other climatic data required such as daily minimum and maximum temperature, relative humidity, wind speed and solar radiation were obtained from State Water Data Centre, Gandhinagar (22 stations) and from Global Weather Data (https://globalweather.tamu.edu/).

CFSR weather is a valuable option for hydrological predictions where conventional gauges are not available (Mehta *et al.*, 2004; Dile and Srinivasan, 2014). Utilizing the National Centers for Environmental Prediction's Climate Forecast System Reanalysis (CFSR) climate data in a watershed model provides stream discharge simulations that are as good as or better than models using traditional weather gauging stations, especially when stations are more than 10 km from the watershed (Fuka *et al.,* 2014). Following that the global weather climatic data were used for the study. Different hydro meteorological and remote sensing data used in the study and their respective sources are presented in Table 1.

ArcMap software developed by ESRI (Environmental Systems Research Institute) was used for arranging all the thematic layers in proper sequence and to perform different operations such as overlaying, intersection etc. to generate SWAT compatible input files and to run the SWAT model. SWAT interfaced with ArcMap 10.2 was utilised for simulating the hydrological processes. SWAT-CUP was used for sensitivity analysis, calibration and uncertainty analysis of the SWAT model. MATLAB software developed by MathWorks was used to train ANN models to predict the stream flow.

Drainage map of the study area was prepared using DEM file. A digital elevation model (DEM) free of sinks (a depressionless DEM) is the desired input to the flow direction process. Steps followed and tools used in ArcMap 10.2 for generation of drainage map are shown in Fig. 2 in form of flowchart. Slope map, soil map and land use-land cover (LULC) map were prepared to give input into the SWAT model.

In SWAT model, streamflow was estimated using SCS curve number method. Model setup of SWAT was done by preparing and giving various inputs to the model. Watershed delineation was done by defining watershed outlet of the study area. Various input files like LULC map, soil map and slope map were used for HRU analysis. HRU definitions were given according commonly used thresholds (Her *et al.*, 2015; Han *et al.*, 2012; Sexton *et al.*, 2010; Srinivasan *et al.*, 2010). In the study, total 17 subbasins and 45 HRUs were generated. After setup of all input files, the model was run for 13 years of calibration period (year 2000-2012). After calibration, the calibrated SWAT model was run for three years (2013-2015) for validation.

Generally, trial-and-error method is adopted to find

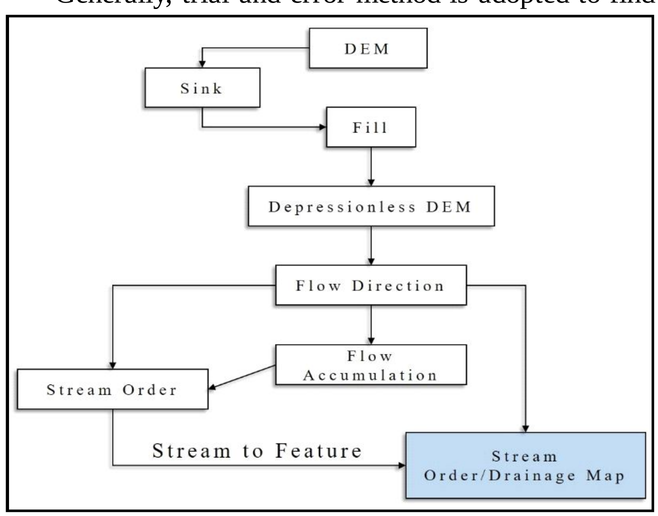

Fig. 2: Flowchart of Drainage map generation in ArcMap 10.2

Table 2: Artificial neural network architecture.

Inputs	Training Algorithm	Hidden layers	Neur-ons	Transfer function	Output
Rainfall	Levenberg Marquardt	Single/ Double	1 to 40	Logsig	Stream flow
Inflow					
Relative humidity					
Max/min temp.					
Solar radiation					

out the significant lag values of the input variable in case of ANN model. Sudheer *et al.*, (2002) presented a statistical procedure that avoids the trial-and error procedure. They reported that the statistical parameters, such as autocorrelation function (ACF), partial autocorrelation function (PACF), and cross-correlation function (CCF), could be used to find out the significant lag values of input variables. With respect to the ACF, PACF and CCF plots, the combinations containing different numbers of input values of runoff and rainfall were considered in the input layer to predict the unique runoff value at the future time step in the output layer of the ANN model. In selection of network architectures, Levenberg Marquardt is considered to be superior for rainfall-runoff prediction studies and it mostly outperforms

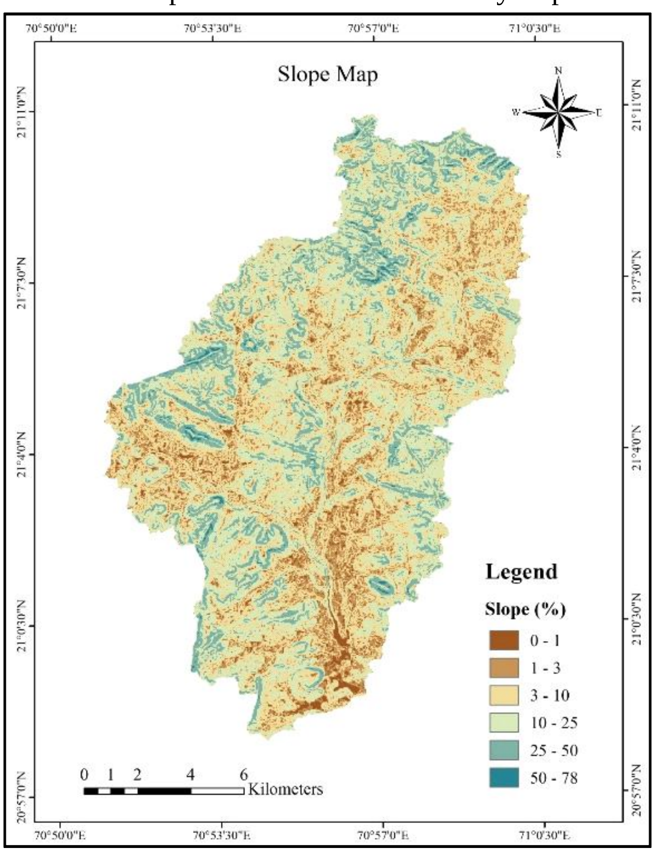

Fig. 3: Slope map of Machhundri watershed.

Table 3: Area under different slope classes of Machhundri watershed.

Sr. No.	Slope class	Area (ha)	Area (%)
1	0 to 1	648.72	3.09
2	1 to 3	2598.05	12.39
3	3 to 10	7660.37	36.54
4	10 to 25	7004.55	33.41
5	25 to 50	2922.64	13.94
6	50 to 78	130.51	0.62
Total		**20964.84**	**100.00**

other algorithms (Solaimani, 2009; Riad *et al.*, 2004; Singh *et al.*, 2016). Feed forward backpropagation neural network with Levenberg Marquardt algorithm was chosen in the study. Different ANN model structures were prepared and tried based on network architecture shown in Table 2. ANN models were developed using daily data of rainfall and runoff of the 12 years period (2001-2012) for training of the model; daily data of year 2000 were used for cross-validation of the model, whereas the daily data of 3 years (2013-2015) were used for testing of the developed model.

Results and Discussion

Various thematic maps were prepared for the study area to use them in SWAT as inputs. The slope map was generated using DEM file borrowed from BISAG. The slope classes were prepared using criteria listed for land

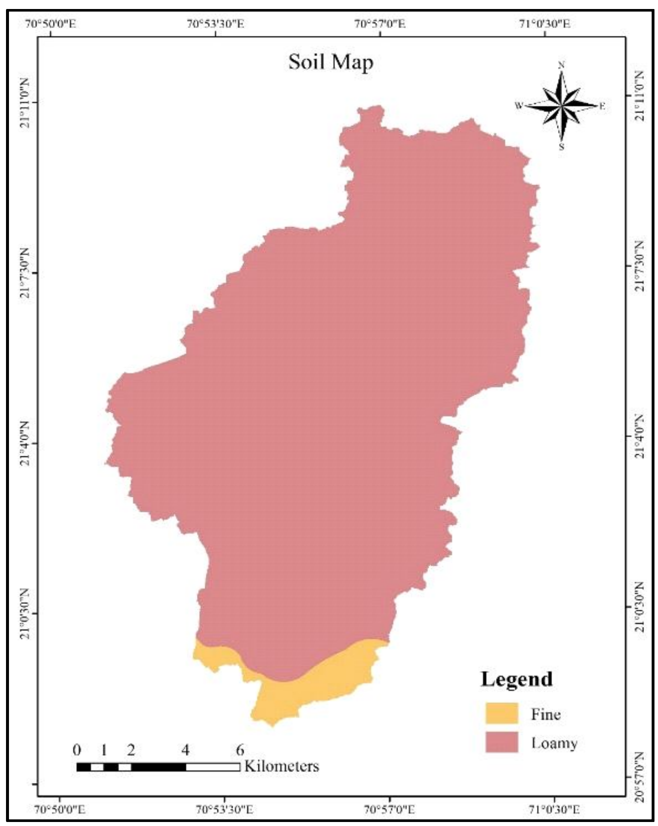

Fig. 4: Soil map of Machhundri watershed.

capability classification (Tejwani, 1976). Percent area in all respective slope classes are shown in Table 3. Study area terrain is having maximum 78% slope. Analysis of the slope map showed that 3.09% and 12.39% area come under 0.1% and 1-3% slope range respectively. 3.10% and 10.25% slope range accounted for 36.54% and 33.41% of watershed area respectively. Whereas 13.94% and 0.62% of area has fallen under 25-50% and 50-78% slope range category. The slope map generated for the study area is shown in Fig. 3. Steeper slopes were found in upstream areas of the catchment.

Soil map was collected from BISAG, Gandhinagar, which was originally prepared by National Bureau of Soil Survey & Land Use Planning (NBSS & LUP) using remote sensing data and ground truth. Soil map was used as the source of soil database and soil grid in the study. After pre-processing using ArcGIS, the soil types obtained for the study area were loamy and fine. The soil map is shown in Fig. 4. Major percentage of watershed area (96%) is having loamy soil texture, whereas the downstream area of about 4% is fine textures soil.

Land use/land cover map was generated using LULC map borrowed from BISAG, Gandhinagar which was prepared using remote sensing image data of IRS P6 from LISS-III sensor of year 2011-12. The watershed was classified into six dominant land use/land cover categories *viz.* fair forest, poor forest, wastelands, agriculture, built-up and water bodies as can be seen from Fig. 5. The GIS analysis of the land use showed that 89.47%, 8.46%, 1.34%, 0.45%, 0.27% and 0.01% area of the watershed were under fair forest, poor forest, water bodies, wastelands, agriculture and built-up respectively. Fair and poor forest classes combined accounted for almost 98% which shows the dominant land cover of forest in the study area.

Fig. 6 shows the drainage map of the study area. As the order of stream increased, number of streams were found to be decreasing; contrary to that, the mean stream length was increased with the increase in order with exception of trunk order. Horton's law of stream lengths supports the theory that geometrical similarity is preserved generally in watershed of increasing order (Strahler, 1964). In the study, stream length decreases with increasing stream order, which supports Horton's law.

After all the inputs were given, SWAT model was run to estimate the streamflow. The initial results were unsatisfactory. After that, sensitivity analysis and calibration were done for SWAT model. From the sensitivity analysis two parameters were highlighted and suggested to use in calibration *i.e.* CN2 (Initial SCS runoff curve number II) and ESCO (Soil evaporation compensation factor). CN2 and ESCO were changed to

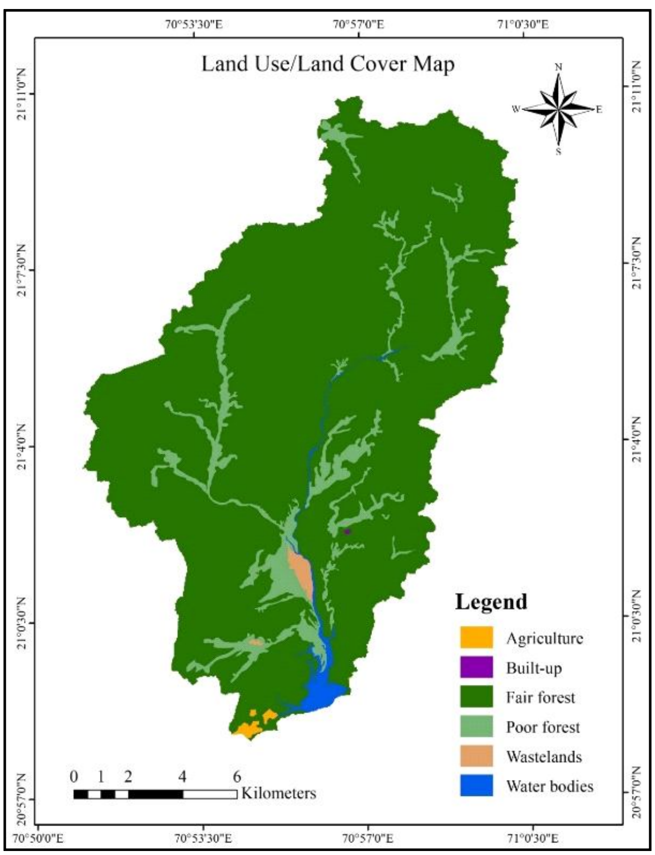

Fig. 5: Land use/land cover map of Machhundri watershed.

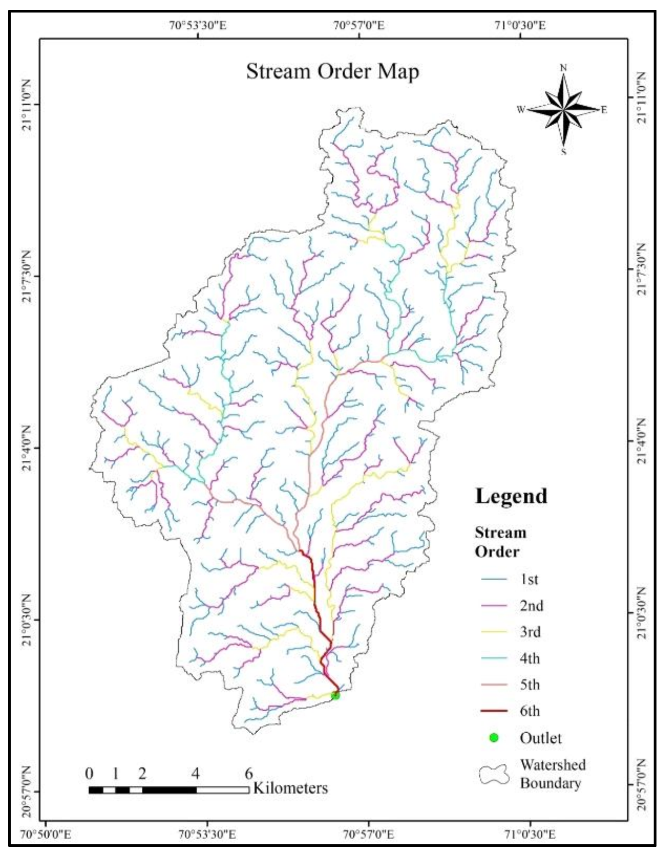

Fig. 6: Stream order/drainage map of Machhundri watershed.

67 and 0.98 from initial values of 78 and 0.95 respectively.

After sensitivity analysis and auto calibration, the SWAT model was again calibrated using the daily dataset for the duration of 13 years (2000-2012) and validated for 3 years (2013-2015). Final simulated streamflow statistics for the Machhundri watershed were found for calibration period as $R^2 = 0.68$, NSE = 57.88 % and

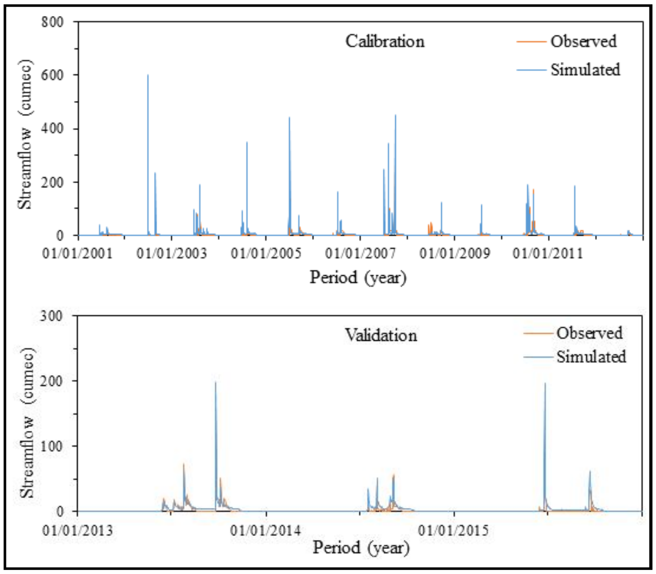

Fig. 7: Hydrographs of observed vs SWAT simulated streamflow during calibration and validation period.

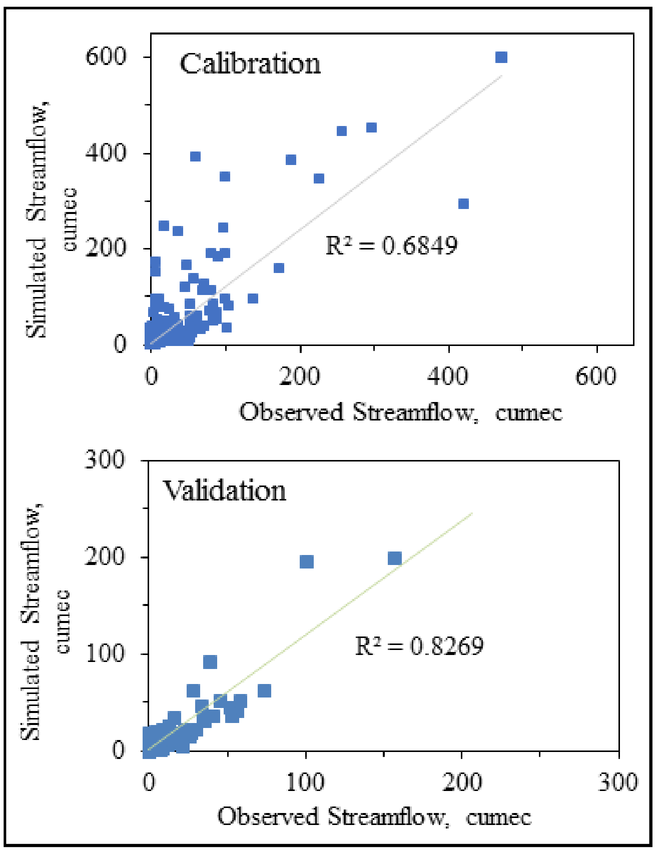

Fig. 8: Scatter plots of observed vs SWAT simulated streamflow during calibration and validation period.

RMSE = 4.94 cumec however for validation period it was improved to $R^2 = 0.83$, NSE = 65.54 % and RMSE = 4.79 cumec. The final simulation improved from the initial values of $R^2 = 0.42$, NSE = 26.27 % and RMSE = 12.86 cumec. Model performance can be judged "satisfactory" for flow simulations if daily, monthly, or annual $R^2 > 0.60$, NSE > 0.50, for watershed-scale models (Moriasi *et al.*, 2015).

Graphical representation of simulated outputs comparing with observed streamflow at outlet point of Machhundri watershed for calibration and validation periods are represented in Fig. 7 to Fig. 8 respectively.

ANN model performance was divided into five different models. At first, all the input variables rainfall (P), maximum temperature (MaxT), minimum temperature (MinT), relative huhmidity (Rh) and lagged streamflow (S) were used in experiment, which was called Exp-I model. Then P, MaxT, MinT and Rh were

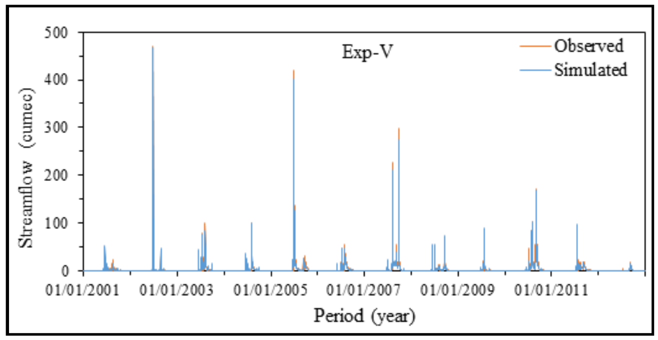

Fig. 9: Hydrograph of observed vs ANN simulated streamflow for Exp-IV and Exp-V during calibration.

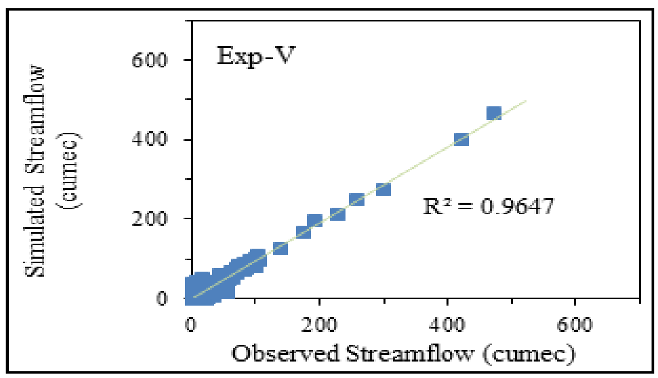

Fig. 10: Scatter plot of observed vs ANN simulated streamflow for Exp-V during calibration.

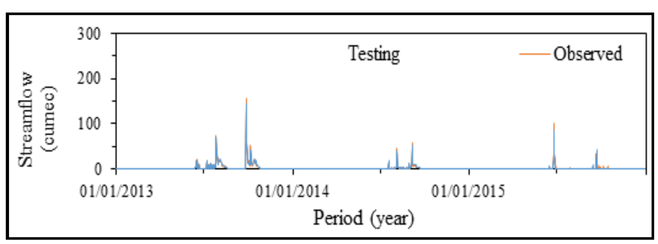

Fig. 11: Hydrograph of observed vs ANN simulated streamflow during testing.

Table 4: ANN model performance for different inputs during calibration period.

Sr. No.	ID	Input variables	Model archi-tecture	R^2	NSE (%)	RMSE (cumec)
1	Exp-I	P, MinT, MaxT, Rh, S-1	5-15-1	0.913	93.89	2.82
2	Exp-II	P, MinT, MaxT, Rh	4-18-1	0.906	92.06	2.15
3	Exp-III	P, MinT, MaxT	3-10-1	0.880	87.48	5.30
4	Exp-IV	P, P-1, P-2	3-20-1	0.894	89.03	4.96
5	Exp-V	P-1, S-1	2-12-1	0.965	96.46	1.88

used as Exp-II. P, MaxT and MinT experiment were named as Exp-III. Finally only rainfall (P) as input was named Exp-IV. Rainfall (P) and lagged streamflow (S) were given Exp V. In every experiment, inputs were tried for various lagged values as well, and streamflow as an input was only used with one or two days lag. Out of all trials of each experiment, best structures' performances during calibration are presented in Table 4.

It can be observed from the Table 4 that the best input variable for runoff simulation was Exp-V using P-1 (one day lagged rainfall) and S 1 (one day lagged streamflow) with 12 hidden neurons. The hydrograph and scatter plot between observed and simulated stream inflow of best performed ANN model for the training period of 12 years (2001-2012) are shown in Fig. 9 and Fig. 10 respectively. Here, it is worth noting that in each experiment, various combinations of lagged input data were tested; out of which, mostly time lag data of CFSR were unable to improve results significantly. Therefore, only up to 1 day and 2 day time lag data of stream inflow and rainfall were used in input combinations, respectively. With R^2, RMSE and NSE values of 0.965, 1.88 and 96.46 % respectively, Exp-V outperformed with all other developed models. Therefore, for validation/testing, Exp-V with 1 day lag of rainfall and streamflow (2-12-1) was

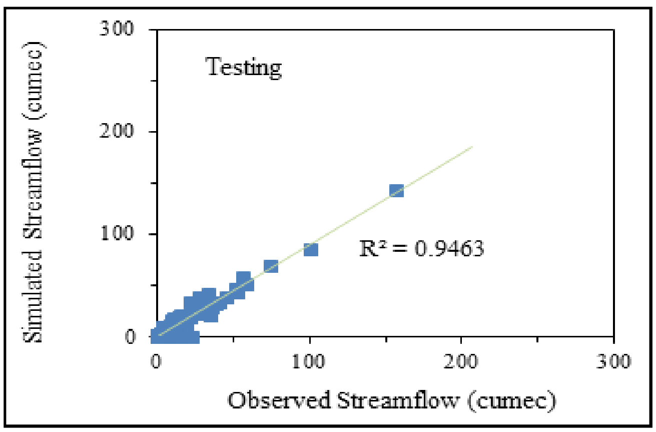

Fig. 12: Scatter plot of observed vs ANN simulated streamflow during testing.

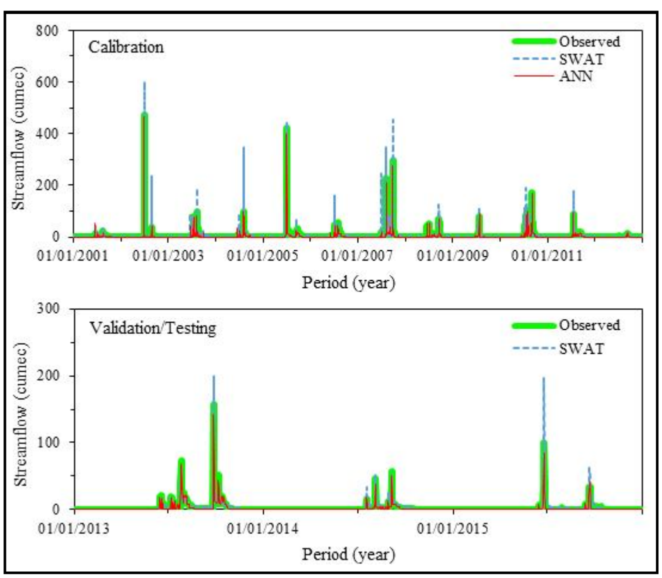

Fig. 13: Hydrograph of observed vs SWAT and ANN simulated streamflow during calibration and validation period.

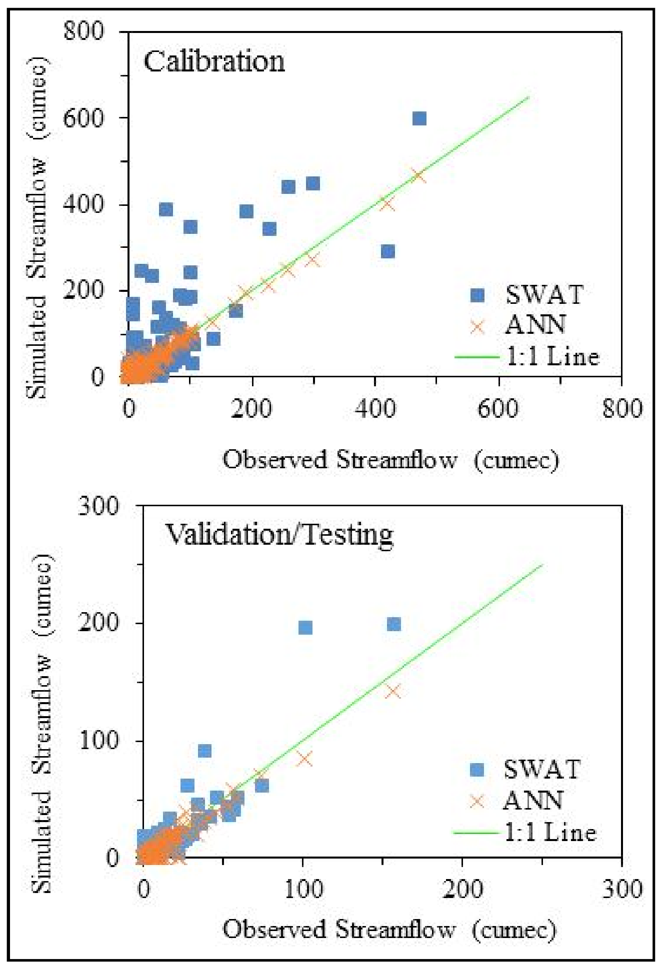

Fig. 14: Scatter plot of observed vs SWAT and ANN simulated streamflow during calibration and validation period.

selected to model the streamflow at outlet of Machhundri watershed.

It can be observed from the Fig. 11 that the performance of the ANN model during testing period with 2-12-1 architecture was very good for simulating peak flow values. ANN model performed well satisfactory for testing period as values were very close to 1:1 line as given in scatter plot (Fig. 12). The R^2, NSE and RMSE values of ANN model were 0.94, 94.34 % and 1.94 cumec respectively for the testing period.

Hydrographs and scatter plots showing the comparison of SWAT and ANN results with observed data for calibration/training and validation/testing periods are given in Fig. 13 and Fig. 14. It can be clearly observed that ANN model performed better than SWAT model during calibration and validation/testing period as well. Comparison indicated that SWAT simulations in the Machhundri watershed were not good enough in forecasting peak flow values. Results of Yagnesh (2017) and Demirel *et al.,* (2009) were in agreement with the results found in this study. The deficiency of not capturing peak values becomes an important issue particularly in the studies of extreme hydrologic events. Although SWAT was able to make overall reliable streamflow simulations. Therefore, SWAT could be advantageous if more local climatic data are available. Morid *et al.,* (2002) reported that the ANN model performed better than the SWAT model during low flow periods. Srivastava *et al.,* (2006) compared the ANN and SWAT model and concluded that the ANN model performed better than the SWAT model. This study results were found to be in well agreement with other researches.

Conclusion

The study compared the performance of the SWAT and ANN models for streamflow prediction in the Machhundri reservoir watershed. SWAT, a physically-based model, provided reliable simulations overall, though it struggled to capture peak flows, highlighting the need for more localized data for improved accuracy. In contrast, the ANN model, using limited data, excelled in simulating both peak and low flows, demonstrating its suitability for streamflow forecasting under data-constrained conditions. These results align with previous research, suggesting that while SWAT remains useful for long-term hydrologic simulations, ANN offers superior accuracy for specific events. The findings underscore the importance of employing complementary modelling approaches for effective water resource management and planning.

Acknowledgement

The authors express their sincere gratitude to the Junagadh Agricultural University (JAU), Water Resources Department (WRD), Gujarat Bhaskaracharya Institute for Space Applications and Geoinformatics (BISAG), State Water Data Centre (SWDC), and National Centers for Environmental Prediction (NCEP) for providing essential resources and data. Their support was instrumental in the successful completion of this study.

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