FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 5 No. 2, June, 2021, pp 173 - 182
DOI: https://doi.org/10.33003/fjs-2021-0502-638

STREAMFLOW SIMULATION: COMPARISON BETWEEN SOIL WATER ASSESSMENT TOOL AND ARTIFICIAL NEURAL NETWORK MODELS

[*1]Haruna Shehu Usman, [2]Abba Aliyu Kasim and [3]Aminu Rabi'u

[1]Department of Science, School of Continuing Education, Bayero University Kano, Nigeria.
[2]Department of Geography and Regional Planning, Federal University Dutsin-Ma, Katsina State, Nigeria.
[3]Department of Geography, Rabi'u Musa Kwankwaso College of Advanced and Remedial Studies Kano, Nigeria.

*Corresponding author's Email: hsusman.sce@buk.edu.ng

ABSTRACT

The present study compared the performance of two different models for streamflow simulation namely: Soil Water Assessment Tool (SWAT) and the Artificial Neural Network (ANN). During the calibration periods, the Nash-Sutcliff (NS) and Coefficient of Determination (R2) for SWAT was 0.74 and 0.81 respectively, whereas for ANN, it was 0.99 and 0.85 respectively. The ANN performs better during the validation period as the result revealed with NS and R2 having 0.98 and 0.89 respectively, while for the SWAT model it was 0.71 and 0.74 respectively. Based on the recommended comparison of graphical and statistical evaluation performances of both models, the ANN model performed better in estimating peak flow events than the SWAT model in the Upper Betwa Basin. Furthermore, the rigorous time required and expertise for calibration of the SWAT is much less as compared with the ANN. Moreover, the results obtained from both models demonstrate the performances of the models in terms of NS and R2 and other model performance indices were satisfactory. Hence, the ANN (black-box model) might emerge as a faster model to implement on water resources management especially in data scarce basins.

Keywords: Streamflow, Basin, SWAT, ANN

INTRODUCTION

Transforming rainfall into runoff is a key process in the hydrological cycle. This process is complex in nature, involving a non-linear relationship between rainfall, runoff, other hydrological processes and watershed characteristics. Runoff not only depends on rainfall but it also depends on various hydrological processes such as interception, evaporation and infiltration (Singh, 1988). These hydrological processes further depend on catchment characteristics and climatic phenomenon. Further, there is considerable amount of uncertainties along with the spatial and temporal variability attributed to the land use and climate change (Rajurkar *et al*., 2004; Ozturk, *et al*., 2013; Niedda *et al*., 2014). Accurate and reliable estimates of rainfall-runoff generation over a given scale is of paramount requirement as part of the information sets that help policy makers make informed decision on water planning and development of water resources (Vaze *et al.,* 2012). Rainfall-runoff modeling is used for water resources assessment, drought and flood analysis over a given scale (Moradkhani & Sorooshian, 2009). Moreover, rainfall-runoff relationships are essential for designing of hydraulic structures such as dam, barrages, flood inundation and flood forecasting studies (Vaze *et al*., 2012).

Traditionally, empirically models which were based on empirical relationship obtained using historical rainfall and stream flow data were used for hydrological modelling. These models do not give any meaningful insight into the governing process and does not consider the spatial and temporal variability in the rainfall- runoff process. Therefore, the conceptual and physically based models have gained popularity over the empirical models. Unlike the physically based model, a conceptual model involves partial representation of the physical dynamics of the hydrological system. Physically based models are based on physical process governing the rainfall-runoff transformation. These models transform rainfall into runoff by solving a number of mathematical equations over the domain and therefore are data extensive.

The recent advancement in technology (hardware and software) have immensely revolutionized the method of hydrologic systems inquiry irrespective of the type of model (e.g., physical-based, conceptual-based, and black-box). There are a number of hydrological models developed for hydrologic modeling and water resources management applications such as MIKE-SHE (Refsgaard & Storm 1995), SWAT (Arnold *et al.,* 1998), HRCDHM (Carpenter *et al.,* 2001), PAWS (Shen & Phanikumar, 2010) and CREST (Wang, *et al.,* 2011).

Amongst the numerous hydrological models developed in the past, SWAT model has been commonly used for the simulation of the hydrological processes. The SWAT model is a process based semi-distributed model which is capable of simulating many hydrological processes. In last few decades, artificial intelligence (AI) techniques have been widely used to simulate the hydrological processes (Rajurkar et *al*., 2004; Nayak et al., 2004). Artificial Intelligence (AI) techniques such as the ANN have emerged as an alternate to the conventional hydrological models. The ability of ANNs to represent the nonlinear relationship between the input variables and the output variables without the necessary knowledge of the underlying system, is arguably their strongest suit, which makes them often more attractive than the other methods (Sivakumar & Berndtsson, 2010). ANN based models have been widely used to simulate various hydrological processes such as rainfall-runoff and sediment yield (Tokar and Johnson, n.d.). ANN models have also been used for flood and reservoir inflow forecasting (Lohani *et al.*, 2012).

A wide range of applicability of ANN and physically based distributed models such as SWAT rises a debate over which model is superior over the other. However, no single model exists that demonstrates a superior performance for all catchments (Nayak *et al*., 2005). There are a number of studies in literature which compare AI based models with the semi-distributed hydrological models. However, there are few studies which compare process-based model (SWAT) and the empirical based model (ANN) (Singh *et al*., 2012).

Most of the researches reported that the ANN model performed better than the process-based model (SWAT) during low flow, whereas, the SWAT model performed better during the peak flow (Morid *et al*., 2002).

Most of the studies compare the performance of SWAT and ANN model for the sediment yield prediction. However, for the rainfall-runoff modeling such studies are limited. In light of this, the main objective of the present study is to compare two models namely: physically based semi-distributed model (SWAT) and an Artificial Neural Network ANN model to provide reliable and accurate estimates of water resource status for informed decision-making in the Upper Betwa Basin, Madhya Pradesh, India.

MATERIALS AND METHODS

Study Area

The Betwa River basin lies between 22° 54' – 26° 00'N and 77°10' – 80°20'E latitudes and longitudes respectively. It originates from the district of Raisen (Madhya Pradesh) at an elevation of about 576 m above mean see level (Figure 1).

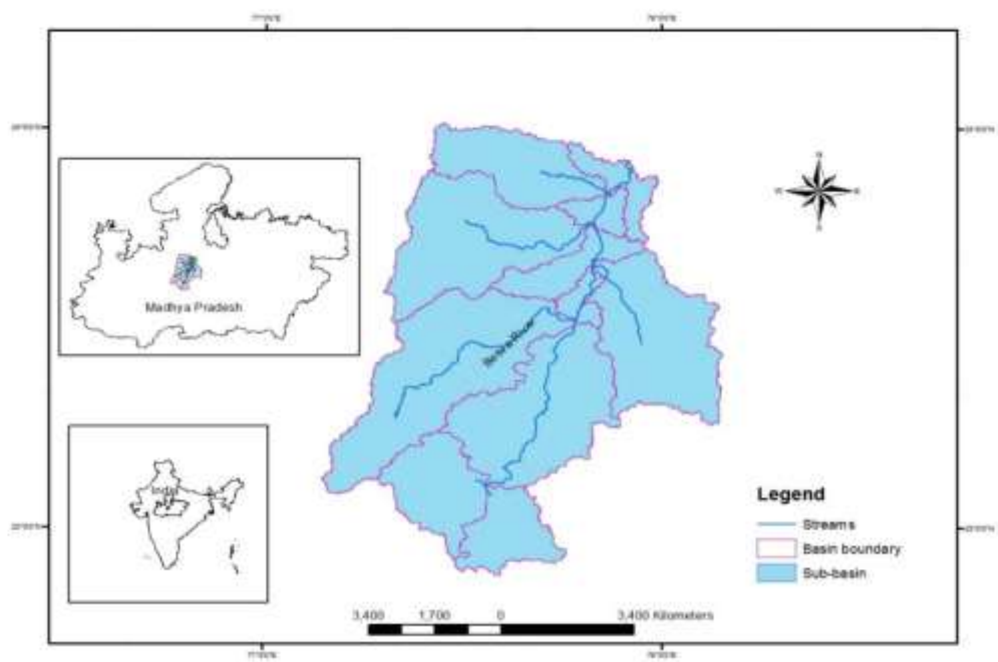

Figure 1: The Upper Betwa Basin, India.

The River has a total length of about 590 km from its origin to the Yamuna River and the total catchment area of the basin is about 44,335 square km. However, the present study will focus on the Upper part of the basin, rather the entire basin.

The climate of the basin is governed by a monsoon weather. The three prevailing seasons are summer (March-May), southwest monsoon (June-September) and winter (November-February), (Ayyar, 2015). The summer is characterized by hot, dry, and windy; low temperatures average at about 25 °C, while high temperatures typically reach about 40 °C. The average annual rainfall is about 1,100m (Ayyar, 2015). Soils in Madhya Pradesh can be classified into two major groups. Fertile black soils are found in the Malwa Plateau, the Narmada valley, and parts of the Satpura Range (Ayyar, 2015). Less-fertile red-to-yellow soils are spread over much of eastern Madhya Pradesh.

RUNOFF MODELLING

The SWAT Model

The SWAT model is a physically-based and semi distributed hydrologic model which was developed to predict the impacts of the inevitable changes in watershed management practices on water, sediment and agricultural chemical yields (Arnold, *et al*.1998; Neitsch *et al.*, 2009; Palazzoli *et al*., 2015). The SWAT model uses two methods for simulating surface runoff, they are the SCS curve number procedure (SCS, 1972) and (Green and Ampt, 1911). Hence, the model was developed to provide a consistent basis for estimating the amounts of runoff under heterogeneous land use and soil types (Rallison & Miller, 1981). However, these two methods differ in their data requirements, the Green and Ampt method requires sub-daily data to estimate runoff while, the SCS curve number requires daily time dataset which was available for the present study. Hence, the SCS curve number equation (SCS, 1972) was used in the present study (equation 1). A more detailed description of Green & Ampt method can be found in (Neitsch *et al*., 2009).

$$Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)} \qquad (1)$$

Where, Q_{surf} = Resultant runoff or rainfall excess (mm), R_{day} = Rainfall depth for the day (mm), I_a = is the initial abstractions which includes surface storage, interception and infiltration prior to runoff (mm) and;
S = is the retention parameter (mm).

Artificial Neural Network (ANN) model

Artificial Neural networks are parameterized non-linear models used for empirical regression and classification modeling. Their flexibility makes them able to discover more complex relationships in data as compared to traditional linear statistical model. ANN is defined as highly interconnected network of many simple processing units called as neurons which are analogous to the biological neurons in the human brain (Sjoberg, 2005). Neurons are an information processing unit that is fundamental to the operation of a neural network, arranged in groups called layer. Neurons in one layer are connected to neurons in adjacent layer only, and the strength of connection between two neurons in adjacent layers is represented by coefficient known as weight. An ANN usually consists of, an input layer, hidden layer(s) and an output layer. The neuronal model also includes an externally applied coefficient called as bias, which has the effect of increasing or decreasing the net input of the activation function, depending on whether it is positive or negative, respectively. Figure 2 shows a schematic diagram of a feed forward ANN with a single hidden layer.

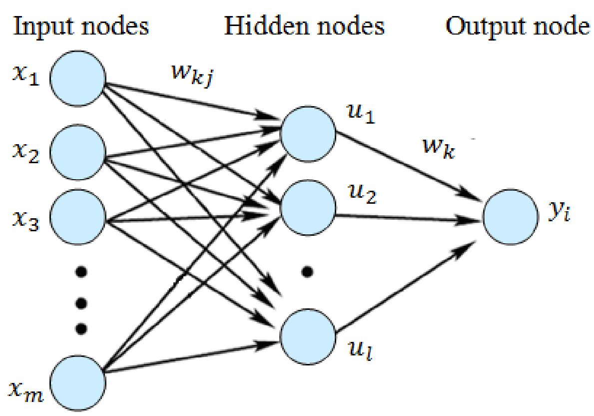

Figure 2: Schematic illustration of feed forward ANN with single hidden layer

A neural network is trained on a set of examples of input and output data. The outcome of this training is a set of coefficients (called weights w_{kj}) and a specification of the functions which in combination with the weights relate the input to the output as shown in figure 2. The training process involves a search for the optimum nonlinear relationship between the inputs and the outputs. ANN is similar to linear regression, in which linear functions of the inputs x_j are operated on by an activation/transfer function so that each input contributes to every hidden unit. Mathematically we can describe neural network by writing the following pair of equations:

$$u_k = \varphi\left(\sum_{j=1}^{m} w_{kj} x_j + b_{kj}\right) \qquad (2)$$

$$y_i = \varphi\left(\sum_{k=1}^{l} w_k u_k + b_k\right) \qquad (3)$$

where φ is hyperbolic tangent transfer function; x_1, x_2,..x_m are the input signals; w_{k1}, $w_{k2}, \ldots w_{km}$ are the synaptic weights of neuron k; u_k is the linear combiner output due to the input signals; b_{kj} *and* b_k are the biases, analogous to the constant that appears in linear regression; and y_i is the output signal of the neuron. The strength of transfer function is in each case determined by the weight w_{kj}. The final output is defined as a linear function of hidden nodes and the constant (Equation 3). The combination of Equation 3 with a set of weights, biases, value of k and the minimum and maximum values of the input variables define the network completely.

Based on the proposed steps made by Dawson & Wilby (2001) preparing ANN to simulate streamflow requires some inevitable decisions which are: selecting the appropriate neural network type, choosing the appropriate training algorithm, selecting the most suitable training periods and identifying the appropriate network structure. Finally, we decided on how to structure pre- and post-process input-output data. Hence, the feed-forward multi-layer perceptron (MLP). ANN is the most widely used type of ANN in hydrological modelling (Wang *et al.*, 2006). Hence, the present study adopted the feed-forward MLP neural network with the backpropagation algorithm for its learning. One scenario was adopted for determining the inputs data to the ANN model. The average rainfall data (Basoda station) in day$_t$ was used. The discharge data in day$_{t-1}$ from 1980-2001 were used for the model training.

Input data

SWAT can run on different ranges of data availability. Clearly, the more the input data the better will be the output results. Table 1 shows data used in the study.

Table 1. Data used to run the SWAT and the ANN model

S/N	Data type	Year	Source
1	Meteorological data	1980-2001	India Meteorological Department
2	Streamflow	1983-2001	India Meteorological Department
3	DEM	2011	http://glcf.umiacs.umd.edu/index.shtml
4	Landsat 8 Image	2012	https://glovis.usgs.gov/
5	Soil map	n.d	NBSSLUP,Nagpur, India

Calibration and Validation

The Sequential Uncertainty Fitting (SUFI-2) (Abbaspour, *et al*., 2007) is used for a combined sensitivity, calibration, uncertainty analysis and validation. Starting with the initial parameter ranges, SUFI-2 is capable of generating different parameter combinations, comparing simulations with observations, and identifying the optimal parameter ranges. Moreover, instead of calibrating model parameters based on hydrologic responses from a single watershed outlet, SUFI-2 is able to simultaneously calibrate parameters based on distributed data within a watershed. Therefore, to fine-tune the calibration process, parameters affecting runoff were first calibrated followed by calibration of variables influencing total flow, and finally calibration of streamflow was performed in SUFI-2.

Calibration and validation analysis were done using the SWAT-CUP 2012 interface for the whole catchment area. SWAT-CUP is an interface that was developed for SWAT model. Using this generic interface, any calibration/uncertainty or sensitivity program can easily be linked to SWAT.

Model evaluation indices

Statistical indices have been commonly used to measure the accuracy between in situ measurements and simulated estimates. Based on the recommendation by Moriasi *et al*. (2007) four statistical and graphical model evaluation techniques were used: The four statistical performance indicators used in the study are shown in Table 2. These statistical indices are grouped into two main categories based on their applications. The first group, RMSE-observations standard deviation ratio (RSR*)* and Percent BIAS (PBIAS) are used to describe the biases and errors of the simulated runoff by the SWAT model with respect to the observed runoff data. The second group, consist of only the Coefficient of Determination (R^2) and the Nash–Sutcliffe Efficiency (NSE) and they are used to measure the general agreement between the in-situ runoff measurements and the model runoff simulation estimates. Their optimal value and value range are shown in Table 2.

Table 2: SWAT model performance indices used in the study.

Statistical index	Formula	Value range	Perfect value
R^2	$R^2=\{\frac{\sum_{i=1}^{n}(o_i-\bar{o})(p-\bar{p})}{\sum_{i=1}^{n}(o_i-\bar{o})^2]^{0.5}[\sum_{i=1}^{n}(p_t-\bar{p})^2]^{0.5}}\}$	0 to 1	1
NSE	$NSE=[\frac{\sum_{i=1}^{n}(o_i-p_i)^2}{\sum_{i=1}^{n}(o_i-\bar{o})^2}]$	-∞ to 1	1
RSR	$\mathrm{RSR}=\frac{\mathrm{RMSE}}{\mathrm{STDEV_{obs}}}=\frac{[\sqrt{\sum_{i=1}^{n}(o_i-p_i)^2}]}{[\sqrt{\sum_{i=1}^{n}(o_i-\bar{o})^2}]}$	0 to ∞	0
PBIAS	$PBIAS=[\frac{\sum_{i=1}^{n}(o_i-p_i)*100}{\sum_{i=1}^{n}(o_i)}]$	0 to ∞	0

Note* where O_i is the ith observed value for the stream discharge (m^3/s), and P_i is the ith predicted value for discharge (m^3/s), $\bar{O}$ is the mean of observed stream discharge for the entire evaluation time period (m^3/s), and P is the mean of model predicted stream discharge for the entire evaluation time period (m^3/s), and n is the total number of observations.

RESULTS AND DISCUSSION

SWAT Model calibration and validation

Model calibration is inevitable when using physically based hydrological models. This is to reduce the uncertainties usually associated with the model. In total, 12 parameters were considered for the model calibration based on the initial parameter sensitivity analysis and 209 iterations were done to achieve the optimal results. Range and optimal value of parameters during calibration are given in Table 3. The SUFI-2 procedure was used for the calibration of the model at a monthly time scale. Comparison between the simulated and the observed outputs were compared at the same outlet (Basoda) point sub-basin 1.

The evaluation of different objective function for the Upper Betwa Basin is presented in Tables 4a and 4b. The model accurately tracked the observed streamflow for the time periods, though some peaks were under estimated during calibration but under estimated less during validation (Figures 3 and 4). This is attributed to less temporal variability in rainfall during the period of validation. Moreover, the model under estimated streamflow for calibration and validation periods. However, it could be observed in figures 3 and 4 that the under estimation of streamflow occurs during higher flows. However, the SWAT model doesn't always simulate extreme events efficiently, hence the model usually under estimate the largest flow events (Demirel *et al*., 2009).

Table 3: Range and optimal value for parameters during calibration period

S/N.	Parameters	Min.	Max.	Best fitted
1	v_CN2.mgt	90	100	93.7
2	v_ESCO.hru	0.98	1	0.98
3	v_GW_DELAY.gw	16.5	45	33.7
4	v_ALPHA_BF.gw	0.9	1	0.92
5	v_SOL_AWC.sol	0.98	1	0.99
6	v_GWQMN.gw	-1.38	5.23	3.6
7	r_SOL_K.sol	-0.8	0.8	0.56
8	r_SOL_BD.sol	-0.5	0.6	-3
9	a_GW_REVAP.gw	-0.1	0	0
10	v_REVAPMN.gw	0	10	3.9
11	r_OV_N.hru	-0.2	0.2	1.4
12	r_SLSUBBSN.hru	0	0.2	0.13

The performance statistics summary for simulated and observed streamflow of the SWAT model for calibration and validation period is presented in Table 3a and 3b.

Table 4a: Performance evaluation, calibration period.

Method	Period	Time scale	Objective functions			
			R^2	NSE	PBIAS	RSR
SUFI 2	1983-1993	Monthly	0.81	0.74	31.6	0.51

Table 4b: Performance evaluation, validation period.

Method	Period	Time scale	Objective functions			
			R^2	NSE	PBIAS	RSR
SUFI 2	1983-1993	Monthly	0.74	0.71	32.3	0.52

The R^2 which is the degree of collinearity between observed and simulated is 0.74 and 0.81 for both calibration and validation periods (Tables 4a and 4b). Hence, this indicates a good linear relationship between the simulated and the observed data.
The NS for calibration and validation are 0.74 and 0.71 respectively. The calibration and validation values fall within the acceptable levels of performance. Based on the recommendation by Moriasi, *et al*., 2007. values between 0.0 and 1.0 for both calibration and validation viewed as acceptable levels of performance, however, values that are less than or equals to 0.0 show that the observed value is a better predictor than the simulated value which shows unacceptable performance. The PBIAS for both calibration and validation are 31.6 and 32.3 respectively. This could be justified as the model underestimated the streamflow for both calibration and validation periods, (Figures 3 and 4). Furthermore, RSR for calibration period is 0.51 while for validation is 0.52.

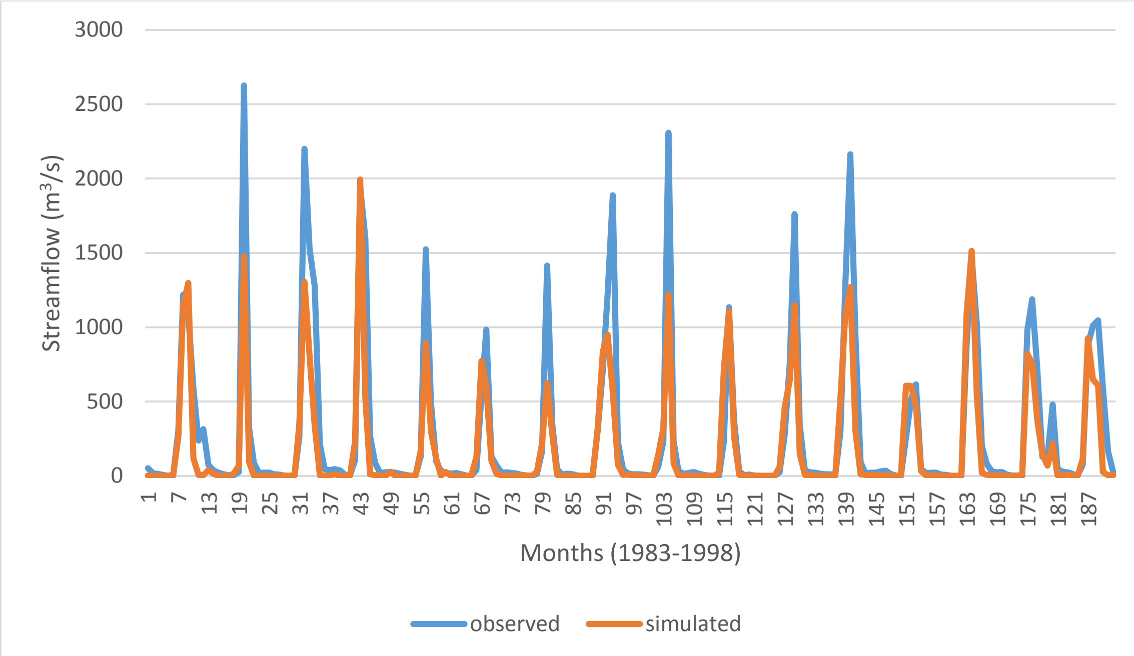

Figure 3: Monthly simulation and observed streamflow during calibration period

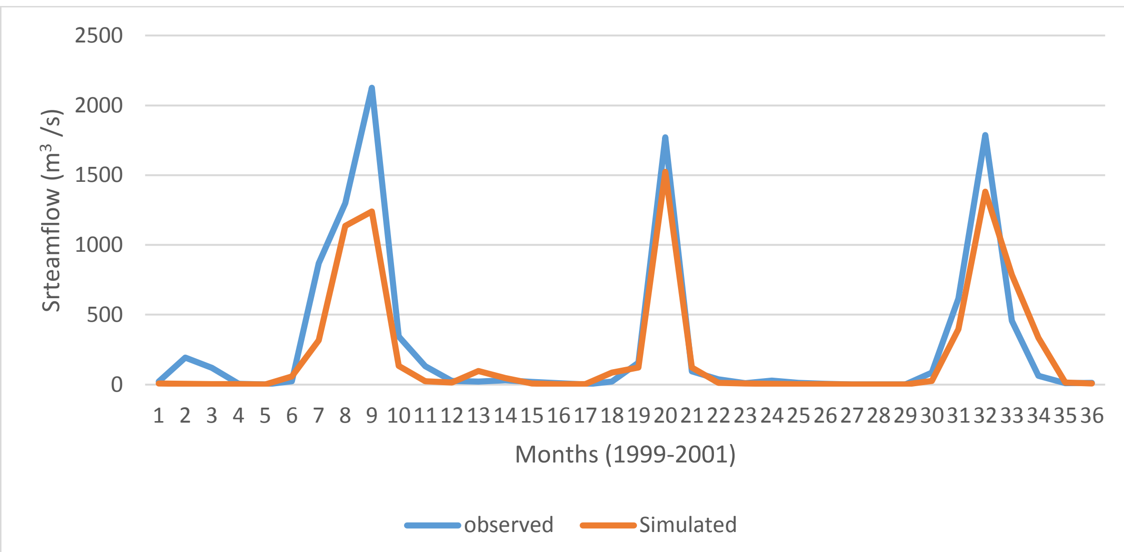

Figure 4: Monthly simulation and observed streamflow validation period.

Conclusively, the performance of the SWAT model results is quite efficient and resourceful in the present study of Upper Betwa Basin. Hydrological models with NS value that is greater than or equals to 0.5 is regarded as satisfactory. Similarly, Moriasi, *et* al., (2007), stated that RSR SWAT model results can be judged as satisfactory if NS is ≥ 0.5 and RSR ≤ 0.7 and PBIAS ±25% for streamflow calibration.

Training, validation and testing of the ANN model

The process of selecting the final ANN structure was based on the trial and error procedure. The process continued until any increment or decrement in number of nodes has no significance in the performance of the neural network. Hence, this is to ensure that the final selected network has minimum complexity and minima MSE. The rainfall data used to run the ANN model represents 20 years monthly scale sets of rainfall values of SWAT output (sub-basin 1). The discharge data from 1980-2001. However, 70% of the observed data was used for the model training, for validation 20% of the data was used, and the remaining 10% of the data was used for model testing. The training phase was terminated when the MSE was minimal. The aim of the ANN model training process is to achieve the best performance measures such as Nash-Sutcliff an R^2. The ANN model reached it optimal level at 606 iterations with 4 hidden nodes. The results of performance evaluation of the ANN model are given in Table 5

Table 5. Results of ANN performance statistics

Model	calibration period		validation period		Testing phase
	NS	R^2	NS	R^2	NS R^2
ANN	0.99	0.85	0.98	0.84	0.98 0.86

Figures 5, 6 and 7 present the observed and simulated streamflow during training, validation and testing phases in the Upper Betwa Basin. There is a very good agreement between the observed and the simulated values. The simulated values during high flow events are nearly perfect than the SWAT model, though during low flow event the model overestimated the flow. Hence, this showed the strength of the ANN model and its efficiency in modelling rainfall runoff events.

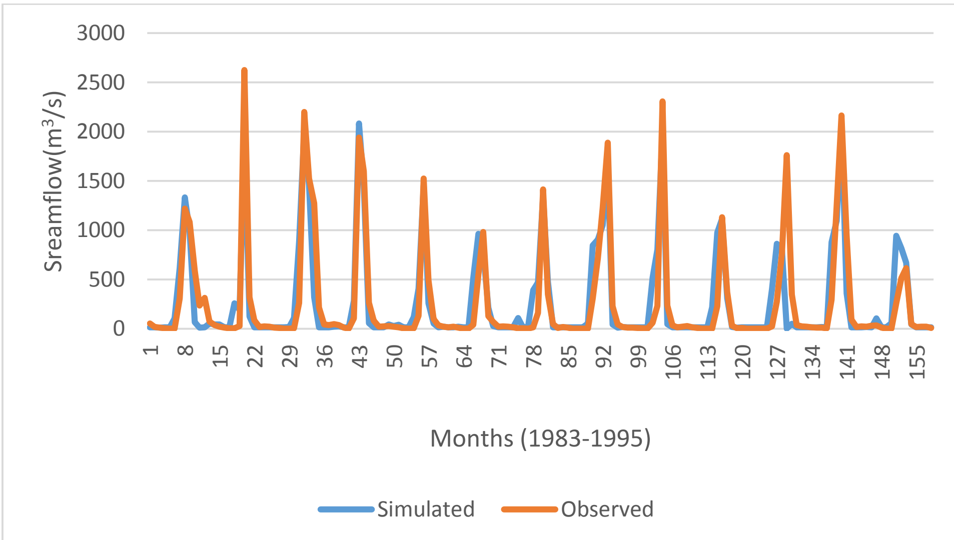

Figure 5: monthly observed and simulated streamflow during training phase

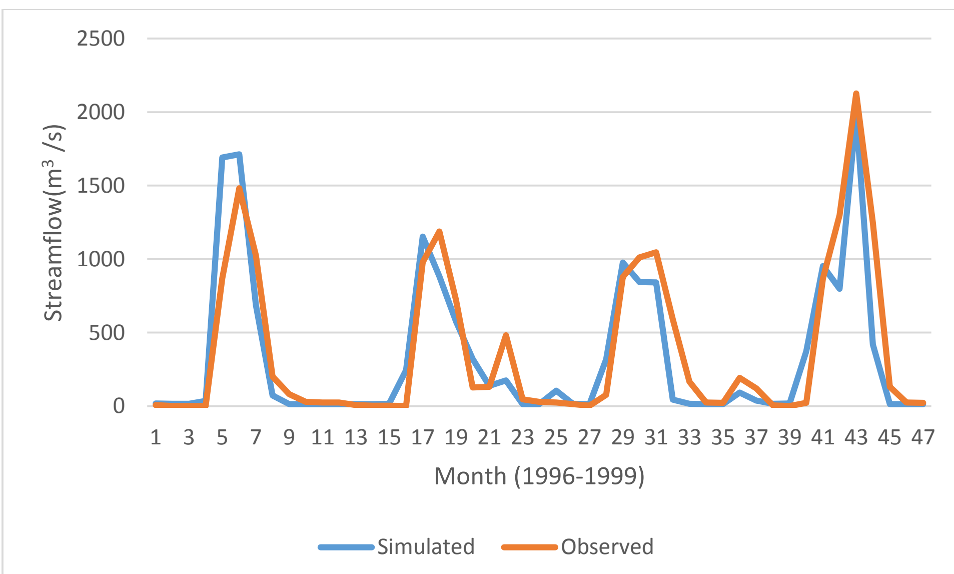

Figure 6: monthly observed and simulated streamflow during validation phase

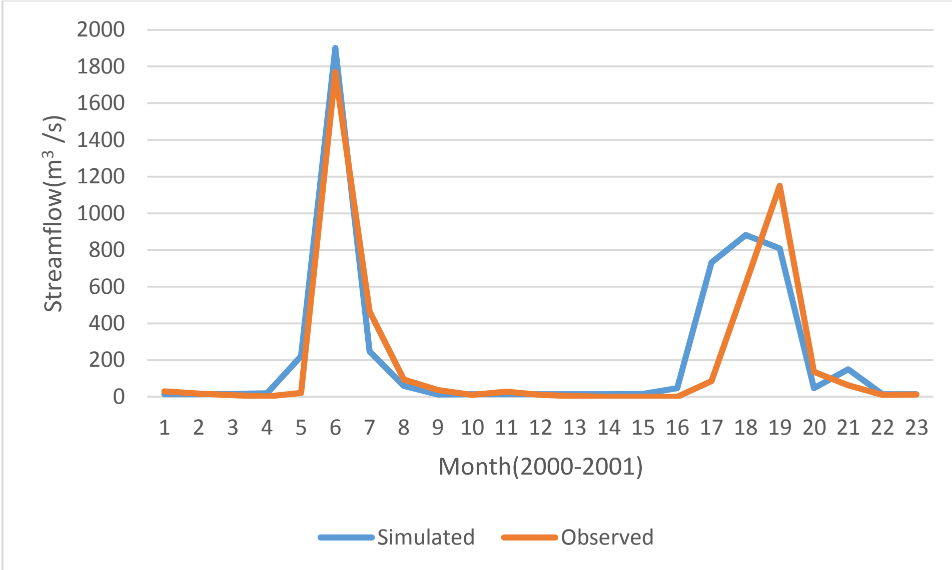

Figure 7: Monthly observed and simulated streamflow during testing phase

Comparison between SWAT and ANN 2

The comparison of the SWAT and ANN model was based on graphical presentations and statistical evaluation criteria. The statistical evaluation is presented in Table 6. It is evident from the result presented in Table 6 that the ANN model outclassed the SWAT model in both calibration and validation periods for streamflow simulation in the Upper Betwa Basin.

Table 6: Comparison of SWAT and ANN model performances

	Calibration period		Validation period	
	Evaluation statistics		Evaluation statistics	
Model	NS	R^2	NS	R^2
SWAT	0.74	0.81	0.71	0.74
ANN	0.99	0.85	0.98	0.89

During the calibration periods the Nash-Sutcliff and R^2 for SWAT were 0.74 and 0.81 respectively while for ANN were 0.99 and 0.85 respectively. Also, during the validation period the ANN performed better as the result revealed with NS and R^2 of 0.98 and 0.89 respectively, while for SWAT were 0.71 and 0.74.

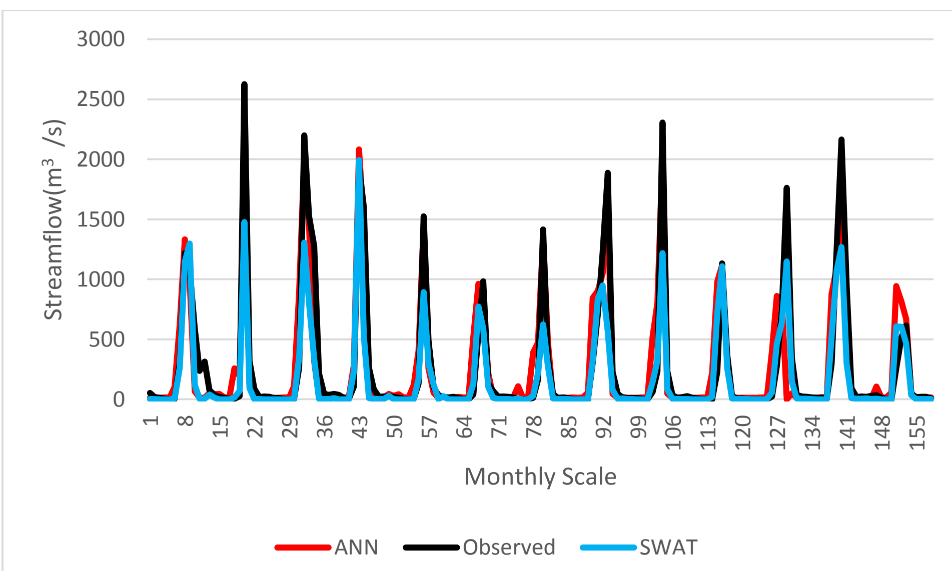

Figure 8: Comparison of SWAT and ANN model performances

Hence, in this context both models show good performance of statistical evaluations. It is evident from Figure 8 that the ANN model is more successful when estimating high flow events than the SWAT model in the present study. However, from the results presented above both models did well for streamflow simulation, but the ANN model outclassed the SWAT model in the estimation of streamflow in the Upper Betwa Basin. Furthermore, the result of ANN model affirms its capability of simulating non-linear relationship such as the case of rainfall-runoff of the Upper Betwa Basin.

CONCLUSION

Rainfall-runoff modelling is dependent on many variables ranging from climatic and different physical parameters such as elevation, vegetation, land use /land cover. Moreover, these parameters make a non-linear relationship and complex relation for rainfall and runoff. Hence, efficient data set required for modelling physical based models such as SWAT is missing in many watersheds in developing countries. Therefore, based on the results of the two models, advancing use of the ANN model in hydrological modeling despite its short background gives an indication of its emergence and bright future in hydrological modelling. Moreover, one of the advantages of the ANN is, it does not require watershed characteristics and other physical parameters in the modeling process, which reduces the difficulties of modeling the system. Furthermore, the rigorous time required for calibration of the ANNs is much less as compared with the SWAT. The ANN model needs less expertise from the modeler. Moreover, when investigating the response of the hydrological processes of the system as a whole, the physically based model (SWAT) may prove to be advantageous in comparison to the ANNs. So, the black-box models might emerge as a faster tool to implement on hydrological modelling.

REFERENCES

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Srinivasan, R. (2007). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. Journal of hydrology, 413-430.

Arnold, J. G., Srinivasan, R., Muttiah, R. R., & Williams, J. R. (1998). Large area hydrological modelling and assessment part 1: model development. J. Am. Water Resources. Assoc., 73-89.

Ayyar, N. P. (2015,823). Encyclopedia Britannica. Retrieved from http://www.britannica.com/place/Madhya-Pradesh

Carpenter, T. M., Georgakakos, K. P., & Sperfslage, J. A. (2001). On the parametric and NEXRAD-radar sensitivities of a distributed hydrologic model suitable for operational use. Journal of Hydrology, 169-193. change on the hydrology of a rural. Journal of Hydrology,97-109

Dawson, C. W., & Wilby, R. L. (2001). Hydrological modelling using artificial networks. Progress in Physical Geography, 80-108

Demirel, M., Venancio, A., & Kahya, E. (2009). Flow forecast by SWAT model and ANN in Pracana basin, Portugal. Advances in Engineering Software, 467-473.

Lohani, A. K., Kumar, R., & Singh, R. D. (2012). Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. https://doi.org/10.1016/j.jhydrol.2012.03.031

Moradkhani, H., & Sorooshian, S. (2008). General Review of Rainfall-Runoff Modeling: Model Calibration, Data Assimilation, and Uncertainty Analysis. In S. Sorooshian, K.-L. Hsu, E. Coppola, B. Tomassetti, M. Verdecchia, & G. Visconti (Eds.), Hydrological Modelling and the Water Cycle (Vol. 63, pp. 1–24). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-77843-1_1

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model Evaluations Guidelines for Systematics Quantification of Accuracy in Watershed Simulations. T. ASABE, pp. 885-900.

Morid, S., Gosain, A. K., & Keshari, A. K. (2002). Solar Radiation Estimation using Temperature- based, Stochastic and Artificial Neural Networks Approaches. Hydrology Research, 33(4), 291–304. https://doi.org/10.2166/nh.2002.0009

Nayak, P. C., Sudheer, K. P., Rangan, D. M., & Ramasastri, K. S. (2005). Short-term flood forecasting with a neurofuzzy model. Water Resources Research, 41 2517-2530.

Nayak, P. C., Sudheer, K. P., Rangan, D. M., & Ramasastri, K. S. (2004). A neuro-fuzzy computing technique for modeling hydrological time series. Journal of Hydrology, 291(1– 2), 52–66. https://doi.org/10.1016/j.jhydrol.2003.12.010

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2009). Soil and Water Assessment Tool Theoretical Documentation Version 2009. Texas: Grassland, Soil and Water Research Laboratory, Blackland Research Center.Watershed Hydrology. Water Resources Publications, 809-846.

Niedda, M., Pirastru, M., Castellini, M., & Giadrossich, F. (2014). Simulating the Hydrological Response of a Closed Catchment-lake System to Recent Climate and Land-use Changes in Semi-arid Mediterranean Environment. *Journal of Hydrology*, 732-745.

Ozturk, M., Copty, N. K., & Saysel, A. K. (2013). Modeling the impact of land use change on the hydrology of a rural. *Journal of Hydrology*, 97-109

Palazzoli, I., Maskey, S., Uhlenbrook, S., Nana, E., & Bocchiola, D. (2015). Impact of prospective climate change on water resources and crop yields in the Indrawati basin, Nepal. AgriculturalSystems,133,143–157. https://doi.org/10.1016/j.agsy.2014.10.016

Rajurkar, M. P., Kothyari, U. C., & Chaube, U. C. (2004). Modeling of the daily rainfall- runoff relationship with artificial neural network. Journal of Hydrology, 18.

Refsgaard, J. C., & Storm, B. (1995). MIKE SHE In: Singh, V.P., (Ed.), Computer Models SCS. (1972). Section 4: Hydrology in National Engineering Handbook.

Shen, C., & Phanikumar, M. S. (2010). A process-based, distributed hydrologic model based on a large-scale method for surface–subsurface coupling. Advances in Water Resources, 33,1524–1541

Sivakumar, B., & Berndtsson, R. (2010). Advances in Data-Based Approaches for Hydrologic Modelling and Forecasting. Singapore: World Scientific Publishing Co. Pte. Ltd.

Sjoberg, J. (2005). Mathemetica Neural Networks "Train and Analyze Neural Networks To Fit Your Data". Illinois: Wolfram Research Inc.

Tokar, A., & Johnson, P. (n.d.). Rainfall-Runoff Modeling Using Artificial Neural Networks. 8. Vaze, J., Jordan, P., Beecham, R., Frost, A., & Summerell, G. (2012). Guidelines for rainfall-runoff modelling: Towards best practice model application. eWater Cooperative Research Centre.

Vaze, J., Jordan, P., Beecham, R., Frost, A., & Summerell, G. (2012). *Guidelines for rainfall-runoff modelling: Towards best practice model application.* eWater Cooperative Research Centre.

Wang, W., Van Gelder, P. H., Vrijling, J. K., & Ma, J. (2006). Forecasting daily streamflow using hybrid ANN models. Journal of Hydrology, 383-399.

©2021 This is an Open Access article distributed under the terms of the Creative Commons Attribution 4.0 International license viewed via https://creativecommons.org/licenses/by/4.0/which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is cited appropriately.