Comparison of a Hybrid Neural Network and Semi-distributed Simulator for Stream Flow Prediction

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Abstract Hydrological models are widely used for the simulation of stream flow in order to aid water resources planning and management in catchment or river basin. Numerous hydrological models have been developed based on different theories. Performance of such models depends on hydro-climatic setting of a catchment. In the present study, performance of a widely used physically based distributed model known as Soil and Water Assessment (SWAT) and a data-driven model, namely hybrid artificial neural network (HANN), has been evaluated to simulate stream flow in an arid catchment located in the south of Iran. Data related to topography, hydrometeorology, land cover, and soil were collected and processed for this purpose. The models were calibrated and validated with same time period to evaluate the advantage and disadvantages of different models. The results showed SWAT outperformed HANN in terms of relative errors such as Nash-Sutcliffe efficiency and percent of bias during model validation. Other error indicates, namely root mean square error (RMSE), mean square error, and mean relative error (MRE), were found close to zero for SWAT during both model calibration and validation. The study suggests that both models have their own promising flow prediction due to their own features and capabilities for daily flow.

Keywords SWAT · Hybrid neural network · Hydrologic modeling · Streamflow

1 Introduction

Estimation of mean and seasonal or daily fluctuation of stream flow is essential for water managers, planning authorities, and disaster mitigation authorities. Long-term simulation of stream flow in catchment or river basin is also required for water

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resource management, sustainable development, evaluation of hydrologic cycle, and related details such as the storage capacity, power generation, release pattern for irrigation, and municipal demands [1]. These pieces of information are particularly important for arid region, where less reliability of stream flow due to little and erratic rainfall is a major concern. Water scarcity is a common problem in such region. At the same time, erratic rainfall often causes prolonged drought or severe flood in such region. It is anticipated that global-induced climate change will make the water resource management in arid or semiarid region more challenging in near future.

Iran is facing increasing challenge due to aridity in recent years. Declination of groundwater and reduction of freshwater resources is a growing concern in the country. The literature review shows that Iran is a water-deficit country since 1999. The World Water Council [2] ranked Iran as one of the highest water stress country in Asia. The increasing water scarcity compelled Iranian government to accept international help [3]. The recent policy of Iranian government is to use new technologies for the evaluation of water resources in order to aid better planning and management of this precious resource.

As a background, in previous decades, the application of digital calculators has over whelmed sophisticated circulation for rainfall-runoff visualization in hydro-logical sciences. In the field of hydrology, privileges of using digital calculators can be proceeded to vast numbers of consequent calculation and to be able to respond to an answer whether it is 'positive' or 'negative' and to be specifically designed interrogations [4]. Hence, the development or application of hydrological tools is a challenging topic owing to monitor of hydrological phenomena [5]. To date, the applicability of various kinds of hydrological tools is a concern owing to have a review on the advantages and disadvantages on such subjects such as streamflow-modeling and attributed topics such as prediction of peakflows and the capability of the runoff volume prediction. Therefore, the availability of different hydrological tools is required to this application for regional and global scales owing to explore the compatibility and applicability in regard to specific objectives in water projects.

Hydrological models are generally used for evaluation of available water resources in a catchment or river basin. Various lumped, semi-distributed and distributed models have been proposed for catchment stream flow simulation and water budgeting. Models have been developed based on knowledge or data. In knowledge-based model, conceptuality on physical relation between stream flow and various hydro-meteorological variables and catchment physical properties are established. On the other hand, in data-driven model, statistical relation between stream flow and various hydro-meteorological variables is established. Models based on both concepts have been found suitable in simulation of stream flow in different parts of the world. However, both the modeling approaches have their own advantages and disadvantages. Suitability of a modeling approach depends on various factors including hydro-meteorology of the region, catchment type, and various catchment properties. Therefore, it is always suggested to use more than one model to assess the performance in order to select the most suitable model for simulation of stream flow. Therefore, selection of most suitable model by

comparing various models is considered as one of the most challenging tasks for hydrologist [6–11].

Recently, two groups of hydrological models are increasingly used for stream flow simulation, namely data-driven and knowledge-driven models. In this research, a knowledge-driven model known as soil and water assessment tool (SWAT) and a data-driven model known as hybrid artificial neural network (HANN) were used to assess their performance in simulating stream flow in Roodan River Basin located in arid region of Southern Iran. Both the models were used to simulate daily stream flow in order to evaluate their performance in simulating various properties of stream flow. It should be noted that there are not too many research for comparison of flow accuracy between SWAT and data-driven techniques [12]. Demirel et al. [12] compared the performance of SWAT and data-driven technique in simulating stream flow of a small basin located in temperate climate. They reported that data-driven model was more successful than SWAT in term of forecasting the peak flows. Srivastava et al. [13] explored the capability of a data-driven tool and SWAT in an agriculture watershed. They reported that monthly runoff prediction capability of data-driven model outperformed SWAT. They proposed less capability of SWAT is due to its weakness in using snowmelt procedure during winter. Morid et al. [14] compared the performance of SWAT and a data-driven model for simulating daily runoff in a snowbound ungauged catchment in Iran. They reported that the performance of both models was more or less same, but the data-driven technique outperformed the SWAT in simulating low stream flows; meanwhile, SWAT simulated the high flows better. The often contradictory results as mentioned above emphasize the need of comparison of different hydrological models.

Stream flow modeling of Roodan River Basin is highly crucial due to increasing water stress in the context of increasing population, urbanization, and unmanaged changing ecosystem [15, 16]. Few studies have been carried out on hydrological modeling in south Iran. This study is the consequent of the previous research in Roodan River Basin [17, 18]. It can be expected that present study will help to identify suitable hydrological model which can be used for the estimation of freshwater flow in arid catchments of south Iran which in turn will help in water resources management and mitigating the impacts of water scarcity.

2 Materials and Methods

2.1 Case Study

Roodan River Basin is located in the Kerman and Hormozgan states of southeastern Iran. The area of the river basin is 10,570 km^2. The basin lies between northern geographical latitude of 26°57′–28°31′ and the eastern longitude of 56°47′–57°54′ (Fig. 1). The annual average rainfall is in the area is approximately 215 mm.
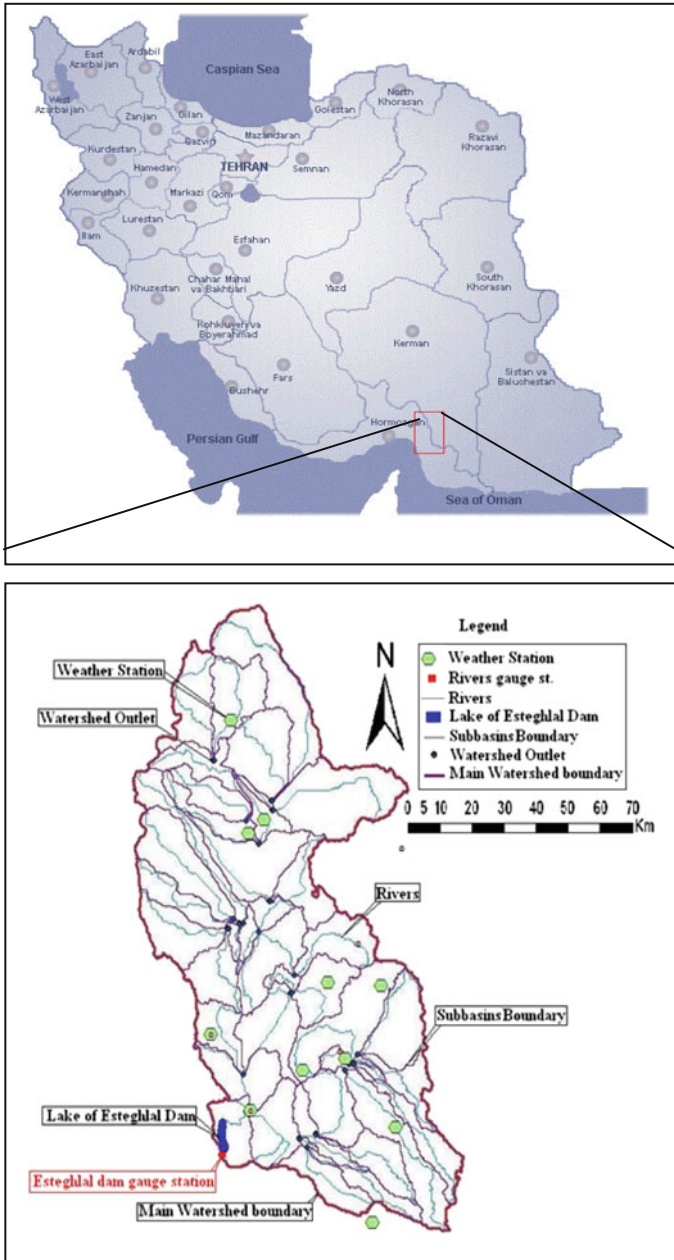
Fig. 1 Site location of Roodan River Basin in Iran

The climate of Roodan is a trade-off from semiarid to arid with high-intensity short-duration precipitation, which provides considerable freshwaters for saving in seasonal and perennial rivers. Major land uses are range brush, mixture of grassland with range brush. Three dams were built in the downstream of basin for water preservation, among which Esteghlal Dam (Minab Dam) is the biggest. Esteghlal Dam located after main outlet of Roodan watershed and delivers major part of freshwater for the city of Bandar Abbas.

2.2 Soil and Water Assessment Simulator

SWAT is a watershed scale hydrologic simulator for visualization of the land management for different scales of basin. It is a public domain hydrological simulator developed by the Agricultural Research Service at the Grassland and Soil and Water Research Laboratory in Temple, Texas, USA [19]. It is widely used for hydrological simulation and environmental impact assessment. SWAT visualizes the hydrologic cycle, freshwaters, return flow, infiltration, evapotranspiration, transmission losses, pond and tank storage, plant/crop growth and irrigation planning, groundwater routing and river routing, nutrient and pesticide loading, and water allocation using with component of meteorological data. This model is applied worldwide and is continuously under development and application owing to reduce of weakness and increasing the applicability in different regions across the globe [19]. Thus, SWAT can be a simulator for monitoring water resources and different management policies in water resource management. SWAT requires hydro-meteorological and catchment physical data such as elevation, land use, and soil. In addition, for better recognition of river streams, digital river map can be used as supplementary data.

In the present study, required data of Roodan river basin were collected and processed for stream flow simulation in the basin. Soil map was prepared from the map of soil distribution, geological map, and available soil samples. The landuse map of Roodan was prepared from Landsat 7 satellite image of the year 2007–2008 and agricultural statistics available from the agriculture organization of Hormozgan, Iran [18, 20].

All available information was used to prepare the Geo-Database for SWAT to visualize the watershed and related features. Meteorological data, namely precipitation and temperature, were used as input to the model. Discharge was modeled based on curve number method of soil moisture condition II for Roodan River Basin [21]. Details of the development of SWAT for Roodan River Basin can be found in [18, 20–23].

2.3   Semi-automatic Calibration Method for SWAT

SWAT conventionally calibrated manually. However, recently a separated program has been developed to calibrate and validate the model, which is known as Sequential Uncertainty Fitting program (SUFI-2). Usually, semi-distributed models such as SWAT need to calibrate many parameters which is very difficult to do manually. Semi-automatic calibration method SUFI-2 provides a faster procedure for SWAT calibration [19]. Moreover, SUFI-2 as semi-automatic calibration method is beneficial for monitoring the calibration procedure and exploring the optimal parameters for validation. Furthermore, SUFI-2 calibration is based on the calculation of potential sources on uncertainties inherent to parameters and variables, conceptual model, and measured data. Propagation of uncertainties in SUFI-2 can be presented at 95 % probability distribution [24]. The criteria of 95 % probability distribution referred to as the 95 % prediction uncertainty (95PPU). Details of the theory and development of SUFI-2 can be found in Abbaspour [25].

In the present study, twenty-six parameters [18], which have direct and indirect influence on flow simulation, are used for calibration of model. SUFI-2 performs number of iterations to find the optimum calibration and optimum parameter ranges for flow simulation. In each iteration, the range of parameters gradually becomes narrower within the parameter space. Usually, a shorter parameter space produces better outcome as the objective function is close to better value. Details of calibration of Roodan River Basin can be found in [18, 20–23].

2.4   Development of Hybrid Network

One of the generations in data-driven techniques is hybrid network, which includes different configuration of the combination of two or more kinds of neural networks or any set of module in input, hidden, or output layers. Hybrid networks are followed to learn of relationships through the data (input–output) and then it generalizes of features to rest of data. Usually, development of data-driven approach includes distinguished stages such as data collection, selection of predictors, and configuration of selected network [26]. To date, various data-driven networks, both simple and hybrid types, have been used in hydrology, meteorology, and water resource management [27, 28].

The HANN used in the present study is the combination of Multilayer perceptron [17]. This configuration provides more flexibility to build hidden layer in creating some structures such as distinguished transfer functions correspond with given neuron [29]. One of the privileges for HANN is speeding up of computation, especially, when there are many input data used for model development.

In the present study, precipitation and discharge data were used as input and output of HANN model. The structure of the network was chosen on tried and error basis. In the present study, hybrid network with three layers, namely the input,
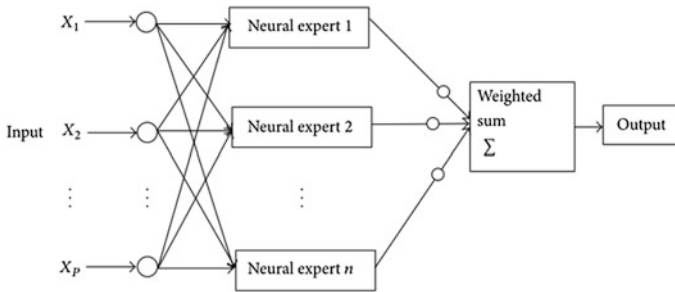
Fig. 2 Presentation of hybrid network for Roodan watershed [17]

hidden, and output layers, were used. The hidden layer is configured into two separated parts, known as neural expert. In other words, the HANN was consisted of a hidden layer configured with nonlinearity and the number of cells in input and output layers (Fig. 2). Usually, the development of network needs transfer functions and training algorithms for hidden and output layers to learn pattern in data. Sigmoild, Linear Sigmoid, and Linear transfer functions were used in the present study with two training algorithms, namely Back propagation and Levenberg–Marquardt [17]. Development of hybrid neural network for Roodan River Basin can be found in [17] in details.

2.5 Criteria for Model's Performance

The performance of SWAT and HANN was evaluated using statistical criteria, namely relative error and absolute error. The relative error offers a relative comparison between the measured and the simulated data such as discharge [13]. In the present study, two methods were used to measure relative error, namely coefficient of efficiency (NS) and percentage of bias (PBIAS) [30]. The value of NS equals to 1 means a complete agreement between the measured and the estimated values. The value of NS equals to 0 presents that all the predicted values are equal to the average value of the observed values. The negative NS value means that the average of the measured data is better than the predicted values. On the other hand, PBIAS is a coefficient to estimate model's capability. A full description of NS and PBIAS is given in [30].

Beside relative errors, absolute errors were used to measure the performance of hydrologic models [31]. In the present study, four methods were used to assess relative error, namely root mean square error (RMSE), the mean-squared error (MSE), the mean relative error (MRE), and mean absolute error (MAE). The RMSE is a dimension value that shows the agreement between the measured and predicted data. RMSE close to zero shows a better performance of model. The MSE value is related to high values (peakflows). MSE should be close to zero for optimal

performance of model. The MRE value is based on the goodness of fit for moderate values. Optimum MRE close to zero shows a better performance modeling. MAE is not weighted toward high-value events (flood, peak flows). Therefore, it calculates all errors from original data without considering the sign [26]. MAE illustrates optimum performance when it is around the zero. Details of the above-mentioned evaluation criteria are discussed in [30, 31].

3 Result and Discussion

3.1 Comparison of SWAT and Hybrid Network

Table 1 summarizes the relative and absolute errors in SWAT and HANN in simulation of stream flow in Roodan River Basin. The table shows that in term of NS, HANN performed better compared to SWAT during model calibration. However, NS during validation was found better for SWAT compared to HANN. SWAT showed a smaller PBIAS in comparison with HANN during both calibration and validation. In terms of RMSE, HANN outperformed SWAT during model calibration (39.4); however, during validation, SWAT performance was better (29.4).

MSE is a better way for evaluating peak flows. Result shows that MSE for HANN was lower during calibration (SWAT = 2631, HANN = 1551). However, during validation, SWAT outperformed HANN in terms of MSE (SWAT = 864, hybrid network = 1036.5). MRE was used to evaluate the performance of models in simulating low-to-moderate flows. Result shows that performance of HANN was better in terms of MRE during model calibration, which was closer to zero (SWAT = 1.6, HANN = 0.88). However, MRE was lower for SWAT during validation (SWAT = 5.95, HANN = 13.4). In terms of MAE, HANN was found to outperform SWAT during both model calibration and validation (HANN = 7.3 − 5.5, SWAT = 11.1 − 5.5).

Some physical properties of catchment have significant influence on low-to-medium flows such as soil features, land cover, and local depression storage.

Table 1 Comparison of SWAT and hybrid network for flow simulation

Index	Calibration–Validation	
	SWAT	Hybrid network
Nash and Sutcliffe coefficient % (NS)	75–64	85–57
PBIAS%	1.5–21.8	4.7–31
RMSE (m^3/s)	51–29.4	39.4–32.2
MSE (m^6/s^2)	2631–864	1551–1036.5
MRE (*100)	1.6–5.95	0.88–13.4
MAE (m^3/s)	11.1–5.5	7.3–5.5

Fig. 3 Measured and simulated daily stream flow (CMS) over calibration
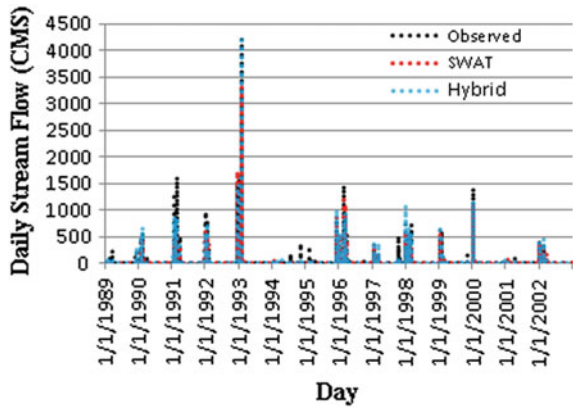
On the other hand, rainfall is considered as the most influential factor for peak or high flows. Therefore, stream flow hydrograph in arid regions is a complex combination of low flows and infrequent peak flows. Therefore, performance of models needs to analyze critically based on various evaluation criteria.

The results show that HANN performed better in terms of NS during model calibration. RMSE, MSE, and MRE were also found closer to zero for HANN in comparison with SWAT during model calibration. On the other hand, SWAT was found to perform better in terms of NS, RMSE, MSE, MRE during model validation. In regard to MAE, both models showed similar performance during model validation. Figure 3 shows the SWAT- and HANN-simulated stream flow in comparison with observed flow during model calibration. The figure shows that both models were successful to simulate an acceptable fluctuation of daily flow. The peak flow during model calibration period was 4209 m^3/s, which were predicted as 3315 and 4184 m^3/s by SWAT and HANN, respectively. Figure 4 shows the SWAT- and HANN-simulated stream flow in comparison with observed flow during model validation. The figure shows that the peak flow during model validation period (1248 m^3/s) was underestimated by both SWAT and HANN. SWAT and hybrid network predicted the corresponding peak flow as 746 and 743 m^3/s, respectively. Highest flows during model calibration and validation are shown in detail in Figs. 5 and 6. The figures show largest flow events for February 1993 and February 2005 during model calibration and validation by SWAT and HANN. Figure 4 shows that HANN outperformed for highest peak flow; meanwhile, both models have similar trend in validation in highest flow event (Fig. 5).

3.2 Pros and Cons of SWAT and HANN

In the present study, SWAT was found advantageous in terms of prediction of stream flow for a long-term period time and meaningful physical parameters guide

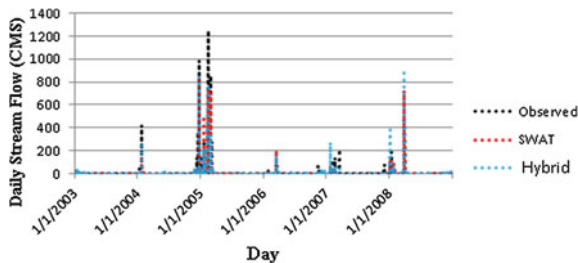**Fig. 4** Measured and simulated daily stream flow (CMS) over validation

Fig. 5 Measured and simulated daily flow for February 1993
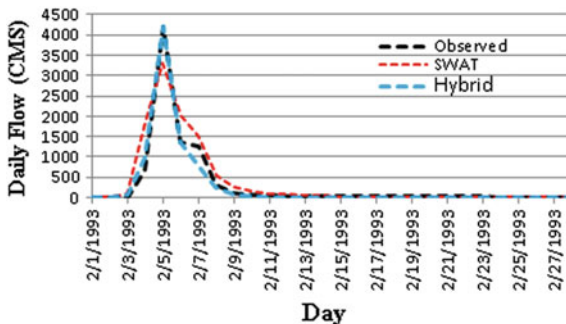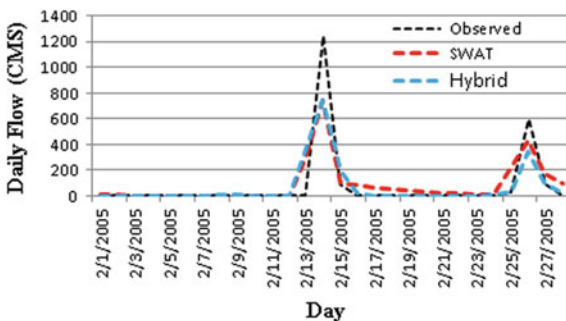

Fig. 6 Measured and simulated daily flow for February 2005

developer for better calibration. The SWAT model is capable to show a visual configuration of Roodan and also it visualizes surface flow besides other water balance component. SWAT can be used as a subsidiary tool with a hydrologist to offer outcomes for monitoring of any management factor such as changing in agricultural area [18]. The drawbacks of SWAT for Roodan might be related to require high-speed digital devices, comprehensive data requirements, and impact of over parameterization in calibration. Moreover, hybrid network is found to be quicker and relatively easier to develop for Roodan on personal device; it does not involve with a collection of variety of data such as SWAT. In addition, HANN needs short time for performing the calculation of simulated data for Roodan. Generally, HANN is capable to model flows with primary knowledge for Roodan

with limited data as input–output pairs. One of the advantages of HANN can be a low cost for Roodan. On the other hand, the disadvantages of HANN are related to low transparency as a data-driven concept for Roodan. Little transparency will cause failure to figure out the interior functions as physically meaning parameters. Another drawback for HANN might be various extensions to be done for Roodan owing to the availability of more options for development based on heuristic circumstances and the outcomes are still unknown for developer. In conclusion, this research suggests the development of current hydrological tools due to comparison and introduction of their applicability in regard to specific regions and objectives.

4   Conclusion

A comparison has been performed for flow simulation on SWAT and HANN. It can be concluded that capability of simulation of flow has been increased with integration of SWAT and semi-automatic calibration (SUFI-2 algorithm). Moreover, HANN is faster for processing and less data demand for application. It can be suggest that SWAT model is more flexible to study the watershed management but HANN model mostly related to the values of flow simulation and hydrological analysis.

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