KSCE Journal of Civil Engineering (2015) 19(1):345-357

DOI 10.1007/s12205-014-0060-y

Water Engineering

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Application of SVM and SWAT Models for Monthly Streamflow Prediction, a Case Study in South of Iran

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Received January 28, 2013/Revised 1st: June 4, 2013, 2nd: December 16, 2013/Accepted January 19, 2014/Published Online July 31, 2014

Abstract

The present study compares the results of the Soil and Water Assessment Tool (SWAT) with a Support Vector Machine (SVM) to predict the monthly streamflow of arid regions located in the southern part of Iran, namely the Roodan watershed. Data collected over a period of 19 years (1990-2008) was used to predict the monthly streamflow. Calibration (training) and validation (testing) were performed within the same period for both the models after the preparation of the required data. A semi auto-calibration was performed for the SWAT model. Also, the best input combination of the SVM model was identified using the Gamma Test (GT). Finally, the reliability of the SWAT and SVM models were evaluated based on performance criteria such as the Nash-Sutcliffe (NS) model efficiency coefficient and the Root Mean Square Error (RMSE). The obtained results from the development of the SWAT model and SVM model indicated satisfying performance in predicting the monthly streamflow in the large arid region. The SWAT obtained NS and RMSE values of 0.83 and 6.1 respectively, and the SVM obtained NS and RMSE values of 0.84 and 6.75 respectively for the validation (testing) period. Results indicate that for high flows of more than 19 (m^3/s), both models predict flow with over and under estimation in the validation (testing) period. Moreover, the SVM has a closer value for the average flow in comparison to the SWAT model; whereas the SWAT model outperformed for total runoff volume with a lower error in the validation period.

Keywords: *streamflow prediction, gamma test, SUFI-2, SWAT, SVM, Iran*

1. Introduction

Rainfall-runoff modeling is one of the most important hydrological processes, especially large-scaled processes (Chang, 2009). Also, nonlinearity and multidimensionality render the modeling of the transformation of rainfall into runoff very complex (Ishtiaq *et al.,* 2010). Hydrological models have an extensive classification but in general, these models have been divided into three groups, which are the empirical or data-driven models, conceptual or gray box models, and physically-based or white box models (Willems, 2000). Empirical or data-driven models do not explicitly use laws and processes, instead they merely relate the input conversion functions to output one (Leavesley *et al*., 2002). The second group consists of conceptual models which are not formed based on all the physical processes but on understanding the behavior of system model's designer. The third group, which includes the theoretical models (physically-based models), try to provide all the existing processes in the required hydrology system through inserting physical senses (Moore *et al.,* 1988). The Soil and Water Assessment Tool (SWAT) is a hydrological model developed by the American Agricultural Research Organization. The SWAT model is a conceptual semi-distributed model according to the basin scale framework. This model consists of various processes including climate, hydrology, nutrients, erosion, vegetation, managerial methods, and flow routing. Therefore, it is popularly applied around the globe (Gassman *et al.,* 2007). Moreover, in recent decades, the development of artificial intelligence techniques, such as Artificial Neural Networks (ANN), Support Vector Machine (SVM) and more, have provided a significant evolution in the predictors of hydrological phenomena (Yang *et al.,* 2009; Kisi *et al.,* 2009; Kocabasa *et al.,* 2009; Kisi and Cigizoglu, 2007). Mathematically, the SVM is used for both classification and regression algorithms, which are formulated through the principles of statistical learning theory by Vapnik, (1995). Due to the wide capability of the SWAT and SVM model regarding water and soil research studies, many studies have been performed all over the world by these models separately (Shepherd *et al.,* 1999; Spruill *et al.,* 2000; Saleh and Du, 2004; Birhanu *et al.,* 2007; Gassman *et al.,* 2007).

In regards to recent studies, the SWAT model was applied by

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Changbin Li *et al.* (2010) to simulate the basin flow and the amount of sediment in China. Rostamian *et al*. (2008) used the SWAT model for modeling the runoff and sediment in the central part of Iran. In Africa, Shimelis *et al.* (2010) assessed the effect of topography, land use, soil, and climate on the hydrology of Ethiopia by evaluating the application of the SWAT model. Tibebe and Bewket (2010) stimulated the monthly surface runoff production and the basin erosion rate of the Keleta region in Ethiopia using the SWAT model. In South Korea, Hong *et al.* (2010) reported spatial and temporal correlation for resolution imaging integrated with the SWAT model. This was due to the fact that soil moisture is an important hydrologic state variable which can affect the actual plant and crop Evapotranspiration (ET), storage capacity for surface runoff, subsurface flow, and recharge of groundwater. Generally, discussions have been made regarding the SWAT soil moisture and new integrated features via calibration and validation periods.

On the other hand, the SVM model is applied for evaluation in hydrology. Bray and Han (2004) used the SVM model for runoff modeling and showed that the SVM model could accurately stimulate the runoff. Han *et al.* (2007) used an SVM model for predicting floods in a basin and compared it with basic models such as simple, trend, multivariate regression, and ANN models. Recently, Jie and Yu (2011) used SVM and ANN for predicting the suspended sediment load of the Kaoping River in Taiwan and results showed that the SVM model had a higher capability than the ANN model. One of the major issues concerning modeling using artificial intelligence techniques is selecting the best combination of the input variables for the model. Thus, various approaches have been used so far, including Principle Component Analysis (PCA), Genetic Algorithm (GA) and many more. GT is one of the approaches that has recently been given attention by many hydrologists (Moghaddamnia *et al.,* 2009). Ahmadi *et al.* (2009) evaluated the capabilities of GT techniques and the theory of entropy to identify effective variables on solar radiation in the Brue basin in the UK. The results showed that the number of required variables for the modeling significantly reduced using GT. Noori *et al.* (2011) reviewed the role of pre-processing the input parameters through PCA, GT, and stepwise regression in the performance of SVM to predict flows. The results indicated higher effectiveness of a pre-processing role in determining input variables.

Few studies have been done to compare SWAT and data-driven models in the past decade. Srivastava *et al.* (2006) applied SWAT and ANN models in a small agricultural watershed for the evaluation of base and surface flow. The results suggested that these models provided a viable alternative approach for hydrological and water quality modeling. Demirel *et al.* (2009) used ANN and SWAT models for predicting the daily flow of the Pracena basin located in Portugal. The results showed that the ANN model was a better model in predicting the peak flow than SWAT model. However, the results of the SWAT model illustrated a much better values for the Mean Squared Error (MSE). Prasantha Hapuarachchi and Zhijia, (2003) compared two types of ANN architectures, namely the Multi-Layer Perceptron network (MLP), and the Radial Basis Function network (RBF) with the SWAT model. However, ANNs gave better results in the subject of the simulation of streamflow; the results revealed that the performance of the SWAT model strictly depends upon the quality of input data (Arnold *et al.* 1998). Morid *et al.* (2002) compared SWAT and ANN for snowy catchments in the subject of snowmelt–runoff simulation in Iran. This research showed that during low flows, ANN is better than the SWAT; however, the SWAT performed better for high flows, especially for the peak flows.

The major aim in this research, which serves as a new contribution, is to compare the efficiency of the SVM and SWAT (version 2009) models for predicting the monthly streamflow of the Roodan basin located in Iran as an arid to semi-arid region. The objectives of this study are (i) monthly streamflow prediction by SWAT and calibration by SWAT-CUP software; (ii) prediction of monthly streamflow by the types of regression SVM (υ*-SVR*) and application of new gamma test technique for finding the best input combination using SVM; (iii) evaluation of the capability of SVM and SWAT in runoff prediction of Roodan watershed.

2. Methodology

2.1 Case Study: Introduction of Roodan Watershed

The study area is located in the southern part of Iran between the Hormozgan and Kerman provinces, i.e. Roodan watershed. The area of catchment is 10,570 km^2 (Fig. 1). The Roodan basin is mountainous in the north and east direction, and plain in the center and south part. During 1978 to 2008, the average annual precipitation was 215 mm. Generally, the soil type in Roodan watershed is a mix of clay, silt, and sand. The environment of Roodan is arid to semi-arid with high intensity and short precipitation. The Roodan watershed land is made up of shrub land, mix grassland with shrub land, rock, irrigated agriculture/orchard farms, and urban areas. In this study, 13 years (1990-2002) were utilized for training (calibration) the models and 6 years (2003-2008) were utilized for testing the models.

2.2 Support Vector Machines

The support Vector Machine is formulated through statistical learning theory principles by Vapnik (1995). The main equation

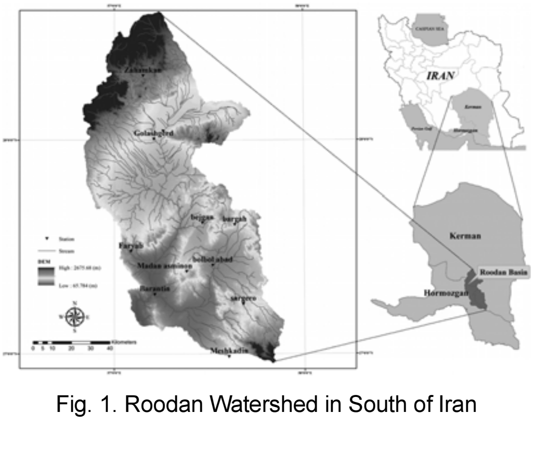

Fig. 1. Roodan Watershed in South of Iran

for statistical learning is as below:

$$y = fX = \sum_{i=1}^{M} w_i \varphi_i(X) = W\varphi(X) \tag{1}$$

where the model output is the sum of M linear; the non-linear convert part of the model is shown by $\varphi(\ )$. This equation is converted into as follows to use the Support Vector Machine model:

$$y = f(X) = \left\{ \sum_{i=1}^{N} w_i K(X_i, X) \right\} - b \tag{2}$$

where K is the kernel function, w_i and b are the model parameters, N is the number of data for training, X_i is the data vector for the network training, and X is the independent vector. The parameters of the model are determined by maximizing the target function. The aim of a linear regression model is to find a linear function in order to do the best interpolation of the training points. Provided that $y=f(x)=\langle w.x\rangle+b$ is obtained based on methods of minimizing the sum of squares, the $\langle w, b\rangle$ parameters can be determined (Cristianini and Shawe-Taylor, 2000).

$$\sum_{i=f1}^{l} (y_i - \langle w.x\rangle - b)^2 \tag{3}$$

In this method, the cost function can be formulated by using the following equation:

$$|\xi|_\varepsilon = |y - f(x)|_\varepsilon = \begin{cases} 0 & if\ |y-f(x)| \le \varepsilon \\ |y-f(x)| - \varepsilon & o.w. \end{cases} \tag{4}$$

The Euclidean norm of a smooth vector space should be minimized with accounting the cost function:

$$\begin{aligned} &\text{Min} && \frac{1}{2}\|w\|^2 + C\left(\sum_i^l \xi_i^* + \sum_i^l \xi_i\right) \\ &\text{Subject to :} && y_i - \langle w.x\rangle - b \le \varepsilon + \xi_i \\ &&& \langle w.x\rangle + b - y_i \le \varepsilon + \xi_i^* \\ &&& \xi_i, \xi_i^* \ge 0 \end{aligned} \tag{5}$$

where, C is the cost coefficient. After solving the equation, it will be:

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) \langle x_i, x\rangle + b \tag{6}$$

This developed equation is supporting vectors for the linear model. Kernel function $K(x, z)$ is the internal production of $\langle\varphi(x), \varphi(z)\rangle$. In various studies, Radial Basis Function (RBF) kernel has been reported as the best kernel. The RBF kernel is shown in Eq. (7):

$$K(x,z) = exp(-\alpha|x-z|) \tag{7}$$

Kakaei Lafdani *et al.* (2013), and Han and Yang (2001) provides further explanations on kernel function.

2.3 Gamma Test (GT)

Gamma test estimates the minimum mean square errors which are obtainable in continuous non-linear models with unseen data (Moghaddamnia *et al.,* 2009). The relationship is established between the set members:

$$y = f(x_1, ..., x_m) + r \tag{8}$$

where r is a random variable. In order to calculate Γ, the linear regression is fitted from p spot to values of $\delta_M(k)$ & $\gamma_M(k)$:

$$\gamma = A\delta + \Gamma \tag{9}$$

where,

$$\delta_M(k) = \frac{1}{M}\sum_{i=1}^{M} |X_{N[i,k]} - X_i|^2 \tag{10}$$

$$\gamma_M(k) = \frac{1}{2M}\sum_{i=1}^{M} |y_{N[i,k]} - y_i|^2 \tag{11}$$

The Delta function calculates the mean squared distance of the k^{th} neighbor (Ahmadi *et al.,* 2009). |.| indicates the Euclidean distance and its corresponding Gamma function, providing that m is the number of the input variables, the combination of 2^m-1 would be among them. Reviewing all these combinations takes a lot of time. The Gamma test can identify the most effective variable in modeling and the best combination of the input variables. Kakaei Lafdani *et al.* (2013), and Han and Yang (2001) provide further explanations on the Gamma test.

2.4 Local Linear Regression

In this method, three points are required to obtain a primary estimate and then using all new updated data for future prediction. The only problem with this model is decision-making for the size of P_{max}, the number of nearest neighbors for considering in local linear model. Selection of P_{max} model for linear regression is called statistical effect explained as below:

$$Xm = y \tag{12}$$

For a neighborhood of P_{max} point, the following equation must be solved:

$$\begin{pmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1d} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2d} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{p_{max},1} & x_{p_{max},2} & x_{p_{max},3} & \cdots & x_{p_{max},d} \end{pmatrix} \begin{pmatrix} m_1 \\ m_2 \\ m_3 \\ \vdots \\ m_d \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{p_{max}} \end{pmatrix} \tag{13}$$

where X is a matrix subsequent $P_{max} \times d$ from P_{max} in the input point in d dimension, xi ($1 \le i \le P_{max}$) are the nearest neighbor points, y output vector corresponding to the input. The m vector of parameters should be determined to provide the best relation between X input and Y output (Remesan *et al.,* 2009).

2.5 Introduction of Soil and Water Assessment Tool (SWAT)

Some hydrologic models have been developed for watershed assessment as reported by Johansen *et al.* (1984), Williams *et al.* (1984), Young *et al.* (1989), Knisel (1980), Arnold *et al.* (1990), and USACE-HEC (2002). Usually, hydrological models have limitations in numerous features of catchment modeling as reported by Saleh *et al.* (2000). Recently, a model has been developed by the U.S. Department of Agriculture (USDA), named Soil and Water Assessment Tool (SWAT). SWAT is a physically based model and it suggests the ability of simulating changes in land management, a high level of spatial detail, continuous-time reproduction, efficient computation, and a limitless number of watershed sections (Lenhart *et al.,* 2002). In SWAT, a watershed is classified into numerous subcatchments, which is subsequently further subdivided into Hydrological Response Units (HRUs) that consist of homogeneous management, land use, and soil uniqueness. The HRUs correspond to the percentages of the subcatchments area. The water balance of each HRU in the watershed is characterized by four storage volumes: soil profile, deep aquifer, shallow aquifer, and snow (Jha *et al.,* 2004). A full report of the SWAT model can be found in Neitsch *et al.* (2005a; 2005b)

2.6 SWAT-CUP Software

The SWAT-CUP software is a public domain program attributed with algorithms through calibration and validation for the SWAT model (Abbaspour and Yang, 2006; Beven and Binley, 1992; Abbaspour *et al.,* 2007; Van Griensven and Meixner, 2006). Yang *et al.,* (2008) reported that the SUFI-2 algorithm is appropriate for the calibration and validation of the SWAT model due to the representation of uncertainties of all sources through parameter uncertainty in the hydrological model. SUFI-2 involves a parameter sensitivity analysis by analyzing which parameters contribute the most to the output variance due to the input changeability (Abbaspour *et al.,* 2007). A comprehensive report of SUFI-2 algorithm and uncertainty procedure can be found by Abbaspour *et al.* (1997), and Huang and Qin (2008).

2.7 Model Results Evaluation and Residual Measures Indices

In this study, graphical evaluations and numerical indicators were used to provide a comprehensive judgment for the SWAT and SVM models, as well comparing them as suggested by WMO (1975). In this study, the Nash-Sutcliffe coefficient of efficiency (NS) was used as relative goodness-of-fit and Root Mean Square Error (RMSE) for absolute measuring (Srivastava *et al.,* 2006).

(1) Nash-Sutcliffe:

$$NS = 1-\left(\frac{\sum_{i}^{n}(Q_{pre}-Q_{obs})^2}{\sum_{i}^{n}(Q_{obs}-Q_{obsave})^2}\right) \tag{14}$$

Generally, the NS coefficient is a development over the correlation-based measures because it is responsive to the measured and simulated averages and variances (WMO, 1975).

(2) Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{(pre)i}-Q_{(obse)i})^2} \tag{15}$$

The RMSE is a dimension measure that shows the agreement between the observed and simulated data. When RMSE is close to zero, it indicates better performance modeling. In addition, in order to study the performance of SVM and SWAT models, the relative error, $E_{relative}$ between the maximum values of the actual flow discharge rate and its corresponding simulated flow discharge (by SVM and SWAT models) were calculated as the following equation:

$$E_{Relative} = \frac{Q_{(m.Sim)_i}-Q_{(m.Obs)_i}}{Q_{(m.Obs)_i}} \tag{16}$$

where, $Q_{(obs)i}$ is the observed value of time i, $Q_{(pre)i}$ is the predicted value of time i, n is the sum of observations, and Q_{obsave} are the average of observed values. Also, $Q_{(m.Obs)i}$ and $Q_{(m.pre)i}$are the maximum values of the actual and predicted flow discharge during i time respectively.

2.8 Flow Prediction using SWAT

Usually, necessary data for the SWAT model development include DEM, land use map, soil map, and meteorological data in a sub-daily or daily scale (Winchell *et al.,* 2010). A mesh-sized map between 50-90 m resolutions is sufficient for the SWAT model (Chaplot, 2005). In Roodan watershed, the DEM was prepared with a 90 m resolution from 1:25000 topographic maps, which were provided by the topography organization of Iran. To obtain accurate simulation in this study, the digital river network burning technique was applied on the DEM. The FAO soil map was used due to the availability of information for needed properties of 5000 soil types in the SWAT model (Faramarzi *et al.,* 2009). Evaluation of the soil map for the distribution of soil types was performed by preparing the geology map (1:25000) and available soil samples from the case study. Then, land use of Roodan was prepared in accordance to the satellite image of Landsat7 (2002), observation of various case studies (2007-2008), available land use map (1:25000), and statistics of agricultural areas from the agriculture organization of Hormozgan, Iran. Generally, information from the available data (satellite images and statistics from the development of agricultural areas) do not show much significant differences in land use, which accounted to less than 2%. As reported by Oeurng *et al.* (2011), changes in land use which are less than 5% is not essential for large-scale modeling. Hargreaves-Samani method was used for potential evapotranspiration. Therefore, only precipitation and temperature data are sufficient for running the model (Neitsch *et al.,* 2005a; 2005b). The daily rainfall-runoff curve number method for soil moisture condition II was used for the calculation of discharge modeling. Water was routed through the channel network by using the variable storage routing method (Chow *et al.,* 1988). Many semi-arid and arid basins have ephemeral channels that take large quantities of streamflow. A procedure for estimating transmission losses for ephemeral streams, which has been incorporated into the SWAT model, can be found in Lane (1983, 1982). Five percent was specified for land-use, soil and slope distribution in HRUs definition stage, which is suitable for large basin modeling, according to Raneesh *et al.* (2010). Roodan watershed was divided into 513 HRUs for whole catchment and 45 sub-basins. At last, the prepared model was run from 1988 to 2008 including a two-year warm-up period.

2.8.1 Calibration Procedure for SWAT Model

Calibration is a fairly tough task for hydrological models, such as SWAT, that include a large range of data and parameters. Therefore, sensitivity analysis is significant to reduce the number of parameters to be optimized throughout the calibration method (Lenhart *et al.,* 2002).

In this study, for finding the sensitive parameters in Roodan watershed, the Latin-Hypercube One-factor-At-a-Time (LH-OAT) method was used before the calibration scheme, which was embedded in the SWAT package model (Van Griensven and Meixner, 2006). The LH-OAT sensitivity analysis method merges the robustness of the Latin-Hypercube sampling with the precision of an OAT design (Van Griensven and Meixner, 2006). Therefore, the full range of all parameters have been sampled, assuring that the changes in the output in each model run can be unambiguously attributed to the input changed.

In this study, twenty-six hydrological parameters were used for sensitivity analysis, as provided in the SWAT (2009) model's user manual (Winchell *et al.,* 2010). In this study, after finding the sensitive parameters in the streamflow simulation, SUFI-2 algorithm was applied in the SWAT-CUP software. The SUFI-2 algorithm calculates the sensitivity of each parameter. It allows users to judge the degree of sensitivity and significance of the parameters for better modeling. A detailed explanation of the SUFI-2 algorithm for calibration and sensitivity analysis can be found comprehensively in Abbaspour *et al.* (2007). Schuol *et al.* (2008) reported that a sensitivity analysis of SUFI-2 algorithm is a more in-depth judge to evaluate parameters for a better simulation. Therefore, many parameters can be analyzed for reviewing the sensitivity for specific objectives during the calibration. Finally, the modeling period was divided in two parts for calibration and validation. Lastly, calibration periods were defined from 1990 to 2002 and the period of 2003 to 2008 was used for validation. In fact, two-third of the data were considered for calibration and one-third of them were considered for validation. The sensitivity analysis for the SWAT model has been reported in Table 1.

The seven highest sensitive parameters have a p-value equal to zero, which is indicated by bold font in Table 1. The effective hydraulic conductivity of the main channel (CH_K2) was assessed as highly sensitive. Indeed, CH_K2 is involved with intermittent tributaries resulting in a contribution of streamflow to the main river. Base flow alpha factor (ALPHA_BF) is another notable sensitive parameter. It is a direct index of groundwater flow response to changes in recharge. Curve number (CN2) was found to be sensitive, possibly due to the application of the soil conservation services-curve number method (SCS-CN) for calculating surface runoff. The available water capacity of the soil layer (SOL_AWC) was found to be sensitive. Besides that, the surface runoff lag coefficient (SURLAG) in Roodan was also evaluated as sensitive. The SWAT model integrates a surface streamflow storage characteristic to lag a fraction of the surface streamflow discharge to the main channel. This procedure is significant when the watershed is in a large scale such as in Roodan watershed.

2.9 Flow Prediction using SVM based on Gamma Test

2.9.1 Model Input Selection by Gamma Test

In order to predict the flow discharge, inputs of average monthly rainfall, average monthly temperature, average monthly runoff, and each of the four time delays were considered as the input model (R_{t-1}, Q_{t-1}, T_{t-1}, R_{t-2}, Q_{t-2}, T_{t-2}, R_{t-3}, Q_{t-3}, T_{t-3}, R_{t-4}, Q_{t-4}, and T_{t-4}) and Q_t was considered as the output model. Parameters whose existence enhanced the complexity of the model and have no significant influence on the results of the model were identified and eliminated. In order to choose effective parameters to predict monthly streamflow, the mentioned inputs were assessed by the GT. To identify the effective input variables, the gamma values were first obtained through GT. Then, one of the input variables was eliminated and the gamma value was calculated for the assumed combination. Therefore, the mentioned variable was entered and another variable was eliminated, and gamma values were obtained for the new combination. Thus, in this way, every variable was deleted once from the input combination. Table 2 illustrates the gamma value for each of the variables from the input combination. As indicated in Table 2, out of 12 variables,

Table 1. List of Sensitive Parameters and Their Ranking for SWAT Model

Sensitivity Rank	Parameter	Description	t-Value*	p-Value*
1	**v_CH__K2.rte	Effective hydraulic conductivity of main channel	-20.5	0
2	v_ALPHA__BF.gw	Base flow alpha factor	12.66	0
3	v_CN2.mgt__SHRB	SCS runoff curve number for antecedent moisture condition type II for Shrub land	11.4	0
4	v_CN2.mgt__MIGS	SCS runoff curve number for antecedent moisture condition type II for Mixed Grassland and Shrub land	5.1	0
5	***r_SOL__AWC(1).sol	Available water capacity of the soil layer	-5	0
6	v_ESCO.hru	Soil evaporation compensation factor	2.46	0
7	v_SURLAG.bsn	Surface runoff lag coefficient	-1.7	0

*t-value and p-value show measure (large absolute value) and significance of sensitivity (close to zero) respectively for each parameter; **v: parameter value is replaced by given value or absolute change; ***r: parameter value is multiplied by (1 + a given value) or relative change (Abbaspour *et al.*, 2007).

Table 2. Identifying the Most Effective Variable for Prediction based on GT

Scenario	Input parameter	Mask	Gamma value	Scenario	Input parameter	Mask	Gamma value
1	*All*	111111111111	0.0040398	8	$All\text{-}R_{t\text{-}3}$	111111011111	0.0040887
2	$All\text{-}R_{t\text{-}1}$	011111111111	0.0050465	9	$All\text{-}RQ_{t\text{-}3}$	111111101111	0.0040814
3	$All\text{-}Q_{t\text{-}1}$	101111111111	0.0046458	10	$All\text{-}T_{t\text{-}3}$	111111110111	0.0042499
4	$All\text{-}T_{t\text{-}1}$	110111111111	0.0046616	11	$All\text{-}R_{t\text{-}4}$	111111111011	0.0036506
5	$All\text{-}R_{t\text{-}2}$	111011111111	0.0060799	12	$All\text{-}Q_{t\text{-}4}$	111111111101	0.0034653
6	$All\text{-}Q_{t\text{-}2}$	111101111111	0.0051154	13	$All\text{-}T_{t\text{-}4}$	111111111110	0.00281
7	$All\text{-}T_{t\text{-}2}$	111110111111	0.0037165				

$R_{t\text{-}2}$ and $R_{t\text{-}1}$ have the highest influence on the flow discharge because eliminating these variables from the modeling will cause the gamma value to increase. In addition, eliminating the variables $R_{t\text{-}3}$ and $Q_{t\text{-}3}$ had no impact on the amount of gamma. Furthermore, the variables $T_{t\text{-}2}$, $R_{t\text{-}4}$, $Q_{t\text{-}4}$, and $T_{t\text{-}4}$ caused a decline in the amount of gamma. Eliminating the other remaining variables had a similar effect in increasing the gamma. Therefore, the variables $T_{t\text{-}2}$, $R_{t\text{-}3}$, $Q_{t\text{-}3}$, $R_{t\text{-}4}$, $Q_{t\text{-}4}$, and $T_{t\text{-}4}$ were eliminated from the input combination.

To determine the best input combination in modeling, various combinations of input parameters were assessed using GT so as to identify the most appropriate combination among the remained variables to predict the flow discharge (note that in selecting the combination, various parameters were tried, including parameters which have been identified as the most effective input variables through GT in prediction). These combinations, along with gamma values, are shown in Table 3.

The results suggested that among the five defined scenarios, the best input combination out of the variables was the combination $R_{t\text{-}1}$, $Q_{t\text{-}1}$, $T_{t\text{-}1}$, $R_{t\text{-}2}$, $Q_{t\text{-}2}$, and $T_{t\text{-}3}$ (Scenario 4). The low gamma value indicated that the data with that combination might possibly provide better results in modeling.

In the next step, the traditional regression model was used among the input and output variables in order to determine the best combination of the input variables. Fig. 2 illustrates the results of correlations among the 12 input variables and the discharge rate (Q_t). As shown in this figure, the variables $R_{t\text{-}2}$, $T_{t\text{-}1}$, $Q_{t\text{-}2}$, $R_{t\text{-}1}$, $T_{t\text{-}2}$, and $Q_{t\text{-}1}$ have the highest correlations with the output discharge. However, it is possible that there is a correlation between some of these variables and one of which may represent one or more variables. Therefore given the covariance matrix, the inputs from the predicted model have been chosen in Table 4. According to Table 4, there is a high correlation between $R_{t\text{-}2}$ and $Q_{t\text{-}2}$; however, according to Fig. 2, there is a higher correlation with the output discharge. Hence, $Q_{t\text{-}2}$ will be eliminated from the input combination. Besides, there is a high correlation between $T_{t\text{-}1}$ and $T_{t\text{-}2}$. According to the Fig. 2, variable $T_{t\text{-}2}$ has a lower correlation than $T_{t\text{-}1}$ with the output discharge; therefore, this variable ($T_{t\text{-}2}$) will also be eliminated from the input combina-

Table 3. Determination of the Best Combination from the Input Variables through GT

Scenario	Input parameter	Mask	Gamma value
1	$R_{t\text{-}1}$, $R_{t\text{-}2}$, $Q_{t\text{-}2}$	100110000000	0.0097917
2	$R_{t\text{-}1}$, $Q_{t\text{-}1}$, $R_{t\text{-}2}$, $Q_{t\text{-}2}$	110110000000	0.0010122
3	$R_{t\text{-}1}$, $Q_{t\text{-}1a}$, $T_{t\text{-}1}$, $R_{t\text{-}2}$, $Q_{t\text{-}2}$	111110000000	0.00084539
4	$R_{t\text{-}1}$, $Q_{t\text{-}1}$, $T_{t\text{-}1}$, $R_{t\text{-}2}$, $Q_{t\text{-}2}$, $T_{t\text{-}3}$	111110110111	0.00047904
5	$R_{t\text{-}2}$, $Q_{t\text{-}2}$	000110000000	0.0099458

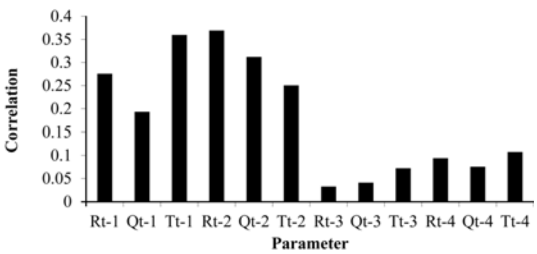

Fig. 2. Correlations among Input Variables and Discharge

Table 4. The Correlation Coefficient Values between Input Variables

	$R_{t\text{-}1}$	$Q_{t\text{-}1}$	$T_{t\text{-}1}$	$R_{t\text{-}2}$	$Q_{t\text{-}2}$	$T_{t\text{-}2}$	$R_{t\text{-}3}$	$Q_{t\text{-}3}$	$T_{t\text{-}3}$	$R_{t\text{-}4}$	$Q_{t\text{-}4}$	$T_{t\text{-}4}$
$R_{t\text{-}1}$	1	**0.887**	-0.54	0.318	0.196	-0.49	0.283	0.185	-0.32	-0.01	0.007	-0.07
$Q_{t\text{-}1}$	0.887	1	-0.38	0.274	0.192	-0.36	0.368	0.311	-0.25	0.031	0.04	-0.07
$T_{t\text{-}1}$	-0.54	-0.38	1	-0.41	-0.29	**0.851**	-0.16	-0.1	0.482	0.096	0.082	-0.01
$R_{t\text{-}2}$	0.318	0.3	-0.41	1	0.887	-0.38	0.318	0.196	-0.49	0.283	0.185	-0.32
$Q_{t\text{-}2}$	0.196	0.2	-0.29	**0.887**	1	-0.38	0.274	0.192	-0.36	0.367	0.311	-0.25
$T_{t\text{-}2}$	-0.49	-0.36	0.851	-0.54	-0.38	1	-0.42	-0.29	**0.853**	-0.17	-0.1	0.485
$R_{t\text{-}3}$	0.283	0.368	-0.16	0.318	0.274	-0.42	1	**0.887**	-0.54	0.318	0.196	-0.49
$Q_{t\text{-}3}$	0.185	0.311	-0.1	0.196	0.192	-0.29	0.887	1	-0.38	0.274	0.192	-0.36
$T_{t\text{-}3}$	-0.32	-0.25	0.482	-0.49	-0.36	0.853	-0.54	-0.38	1	-0.42	-0.29	**0.853**
$R_{t\text{-}4}$	-0.01	0.031	0.096	0.283	0.367	-0.17	0.318	0.274	-0.42	1	**0.887**	-0.54
$Q_{t\text{-}4}$	0.007	0.04	0.082	0.185	0.311	-0.1	0.196	0.192	-0.29	0.887	1	-0.38
$T_{t\text{-}4}$	-0.07	-0.07	-0.01	-0.32	-0.25	0.485	-0.49	-0.36	0.853	-0.54	-0.38	1

tion. In addition, there is a high correlation between the variables Q_{t-1} and R_{t-1}. As Fig. 2 indicates, Q_{t-1}, which has a lower correlation than R_{t-1} with the output discharge, will be eliminated from the input combination. Hence, the determined combination using the regression model was R_{t-1}, T_{t-1}, and R_{t-2}.

2.9.2 The Flow Prediction by SVM Model

In the runoff prediction out of 228 data collection, 156 data (1990-2002) were used in the training model and the rest (2003-2008) were also used for the testing model. In this step, the amount of flow was predicted by two steps through the SVM model: 1. predicting the flow through the SVM model based on the determined combination using GT (GT-SVM), and 2. Predicting the flow through the SVM model based on the determined combination by regression method (Reg-SVM). In addition, the results of the prediction were compared with the results of the LLR model as a benchmark model.

As indicated, to predict using *υ-SVM* and RBF kernel, the optimal values of the parameters C, ε and γ should be determined. In this study, the values of these parameters were determined using the trial and error method. In selecting the optimal values of the parameters, it was found that the model has minimum error in the testing stage using these values. The C and ε parameters had influence on the quality and duration of training. The C parameter keeps a balance between margin maximization and training error minimization. A smaller C results in low pressure; whereas a very large C value causes overfitting of data training. C is useful for controlling the smoothness of the function. The kind of noise in the data, when determinable, directly influences the optimal value of ε. The number of resulting support vectors should be considered as well. The training sets, if insensitive to ε, will not encounter the boundary condition (Kakaei Lafdani *et al.,* 2013). Moreover, the value of the γ parameter influences the occurrence of overfitting and underfitting in the network. When γ increases substantially, it results in overfitting (i.e. the prediction of only the trained data). In this case, the model becomes complex due to the need to consider the distances of all support vectors. When the value of γ drops substantially, under fitting occurs (i.e. the model being unable to predict the trained data), which is caused by the machine ignoring most of the support vectors (Kakaei Lafdani *et al*., 2013). Fig. 3 shows the curve changes of the predicted flow using different values of C. Increasing C values will penalize the errors and hence, the resulting GT-SVM will have a small number of support vectors. According to Fig. 4, the increased value of C from 1 to 4.3 changed the error value slightly from 16.6 m^3/s to 14.1 m^3/s, and then the increase to C=1000 increased the error value to 42.2 m^3/s. Therefore, C=4.3 would be selected.

In addition, Fig. 5 shows the curve changes of the predicted flow using different values of ε. As indicated in the Fig. 5, with an increase in ε value, prediction error increased during the testing period with a constant value (equal to 4.1 m^3/s). Fig. 6 shows the RMSE changes of the GT-SVM model according to various ε values. Fig. 6 illustrates that if the value ε=0.006 is chosen, the GT-SVM model would be able to predict the value of flow discharge with a lower error. Curve changes of the simulated runoff using different values of γ are shown in Fig. 7. As shown in the Fig. 7, by decreasing the value of γ, the predicted flow curve is more inconsistent with the observed flow. Due to the RMSE change curve's correspondence to the different values of γ (Fig. 8), γ=1.5was selected because at this point, the GT-SVM model predicts the flow discharge with a lower error and the error value had no significant change with an increased value of γ. When the γ value is very small, underfitting occurs

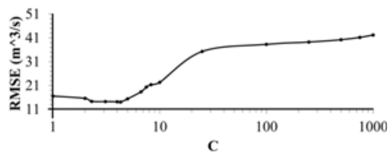

Fig. 4. Determination of Optimal C Value

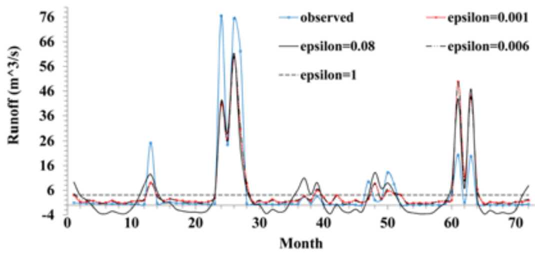

Fig. 5. Observed and Predicted Runoff based on Different ε Values

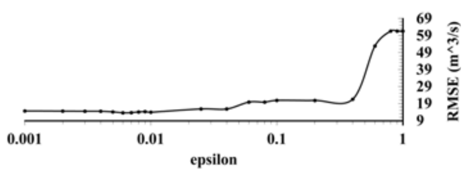

Fig. 6. Determination of Optimal ε Value

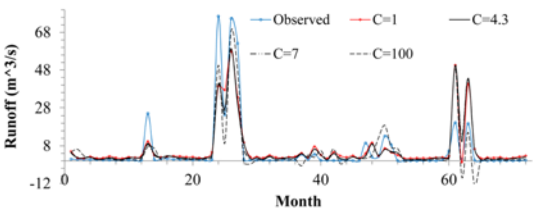

Fig. 3. Observed and Predicted Runoff based on Different C Values

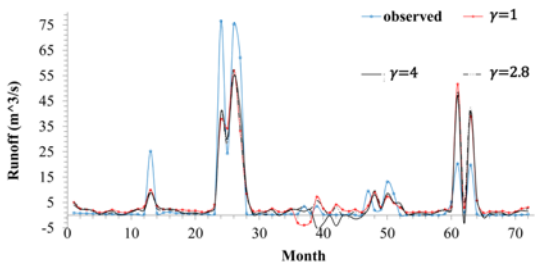

Fig. 7. Observed and Predicted Runoff based on Different γ Values

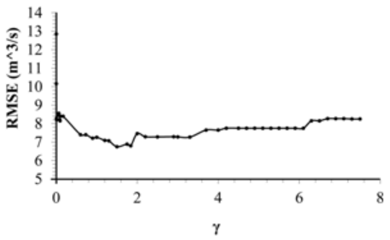

Fig. 8. Determination of Optimal γ Value

because most of support vectors are ignored. Also, a large value of γ increases the complexity of the model and will lead to overfitting.

Therefore, the values of three parameters (i.e. C, ε, and γ) were selected based on the determined combination for the GT-SVM model and the correlation method. The three parameters, C, ε, and γ, were equal to 4.3, 0.006, and 1.5, respectively. For the Reg-SVM model parameters, C, ε, and γ were equal to 9, 0.0085, and 3.4, respectively. The obtained results from flow prediction using the GT-SVM, Reg-SVM, and LLR models are shown in Table 5.

Given the results of Table 5, the determination of the predictors through the regression method (R_{t-1}, T_{t-1}, and R_{t-2}) has been the best model in the training phase of the network. In other words, the performance of the Reg-SVM model was much better than the GT-SVM model during the training period because the Reg-SVM model had a lower RMSE value (4.36 m^3/s) and a higher NS value between the predicted and actual values. However, in the testing period, the model with the determined input combination by the gamma test (GT-SVM) had the best performance (lowest $RMSE$=6.75 m^3/s) compared to the model with the determined combination by the regression method; this indicates the efficiency of the GT model in selecting the input variables in the prediction model.

In addition, Table 5 shows that both the GT-SVM model and Reg-SVM model performed remarkably well in the training and testing stages. Also the GT-SVM model showed better performance over the Reg-SVM and LLR models. While using the GT-SVM model ($RMSE$=5.47 m^3/s) during the training stage, the predicted error is 55.2% lower than LLR model ($RMSE$=12.21 m^3/s). The NS coefficient for the GT-SVM model (NS=0.98) in this stage was 55.56% higher than the NS coefficient for the LLR model (NS=0.63). For the testing period, the GT-SVM model with the lowest RMSE value (6.75 m^3/s) and highest NS value (0.84) was the best model in predicting the streamflow compared to the LLR model ($RMSE$=16.85 m^3/s, NS=0.51).

Table 5. The Results of Training and Testing Stages of GT-SVM, Reg-SVM and LLR

Model	Training			Testing		
	GT-SVM	Reg-SVM	LLR	GT-SVM	Reg-SVM	LLR
RMSE	5.47	4.36	12.21	6.75	8.45	16.85
NS	0.98	0.99	0.63	0.84	0.76	0.51

3. Results

As mentioned during the introduction section, the main aim for this study was to evaluate the physically-based and distributed-parameter SWAT model with the performance of the GT-SVM model for predicting monthly discharge from a large, arid to semi-arid watershed in the southern part of Iran. The results obtained from the prediction using SWAT and GT-SVM models for indices are shown in Table 6.

The results of Table 6 show that SWAT and GT-SVM models have very good performance during training and testing stages. By comparing the performance of SWAT and GT-SVM models during the training stage, it was found that the GT-SVM performed better (NS=0.98) than the SWAT model (NS=0.92). However, it does not mean that the SWAT is weak due to its prediction. In addition, while using the GT-SVM model ($RMSE$=5.47 m^3/s) during the training stage, the predicted error which is 47.9%, was lower than the SWAT model ($RMSE$=10.5 m^3/s). The linear scale plot of the observed and predicted flow is shown in Fig. 9 (training stage). Generally, both of the models have a reasonable accordance trend with the observed data in Fig. 9. As it can be seen from Fig. 9, for the highest recorded flow of the 38th month (Feb/1993), SWAT overestimated the flow in contrast to GT-SVM which underestimated the flow.

By comparing the results during the test of the models, results indicated that both SWAT and GT-SVM models have a high performance in predicting the runoff. The NS coefficient in SWAT and GT-SVM models are close to each other (NS_{SVM}=0.84 and NS_{SWAT}=0.83). This shows that both of the models have a high level of performance. The NS coefficient for the GT-SVM model (NS=0.84) in this stage was 1.2% higher than the NS coefficient for SWAT model (NS=0.83). The absolute prediction error of flow was 9.63% lower through the SWAT model ($RMSE$=6.1 m^3/s) during the testing stage than the GT-SVM model ($RMSE$=6.75 m^3/s).

Generally, both of the models have a reasonable accordance trend with the observed data in Fig. 10. As it can be seen from

Table 6. The Results of Training and Testing Stages of SWAT and GT-SVM Models

Model	Training		Testing	
	RMSE	NS	RMSE	NS
SWAT	10.5	0.92	**6.1**	0.83
GT-SVM	**5.47**	**0.98**	6.75	0.84

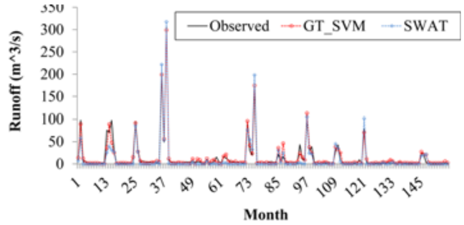

Fig. 9. Observed and Predicted Runoff in the Calibration (Training) Stage

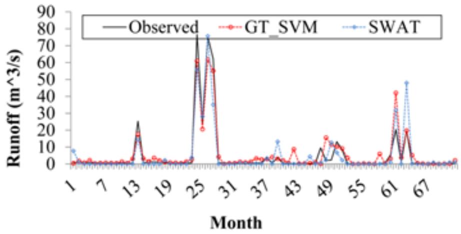

Fig. 10. Observed and Predicted Runoff in the Validation (Testing) Stage

Table 8. Comparing the Maximum Predicted Flow Discharge Values by SWAT and GT-SVM Models

Runoff > 19 m^3/s	SVM	SWAT	Relative Error %	
			SVM	SWAT
25.27	17.61	14.49	**-30.31**	-42.67
76.58	61.01	55.93	**-20.334**	-26.97
24.36	20.64	28.06	-15.28	**15.168**
75.37	61.87	75.65	-17.91	**0.3777**
62.15	55.15	35.08	**-11.27**	-43.56
20.35	42.08	31.83	106.76	**56.397**
19.88	19.8	48.03	**-0.26**	141.58

Fig. 10, SWAT and GT-SVM similarly underestimated the flow for the highest recorded flow of the 24^{th} month (Dec/2004). A comparison between the observed and predicted monthly flow in the validation period is shown in Fig. 11. It can be seen from Fig. 11, predicted flows by GT-SVM and SWAT closely follow the observed data. The scatter plot clearly shows that the GT-SVM has a higher R^2 value (0.9) than the SWAT model (0.8).

Due to the importance of validation period, which shows the generalization of a model, the statistical index for this period was evaluated. Table 7 illustrates the statistical index of observed and predicted runoff. As seen from Table 7, mean streamflow of SWAT is lower than observed data. In addition, the GT-SVM has a higher mean flow during the testing period in comparison with the observed flows.

Also the maximum flow values (more than 19 m^3/s) and its corresponding predicted flow during the testing stage are shown in Table 8 and the relative error of the actual and predicted values have been calculated according to Eq. (20). As indicated in Table 8, while the SWAT model predicted the maximum observed flow (76.58 m^3/s) to be 55.93 m^3/s with a relative error of 26.97% lower than actual value, the GT-SVM model predicted this value to be 61.01 m^3/s with a relative error of 20.33% lower than actual value. In addition, while the GT-SVM model predicted the second max peak to be 75.37 m^3/s with a relative of 17.91% lower than actual value, the SWAT model predicted the same value with a lower relative error of 0.38% higher than the actual value and provided a more accurate estimation of the flow discharge. The results of Table 8 showed that the maximum predicted values through the GT-SVM model are closer to its actual corresponding values than the maximum predicted runoff by the SWAT model. In other words, according to this research, the GT-SVM had higher capability in predicting the flow peak values.

The total observed discharge volume during the training (calibration) stage was equal to 2254.66 m^3/s. The SWAT and GT-SVM models predicted this value as 1754.19 m^3/s and 2298.39 m^3/s, respectively. The predicted flow volume using the SWAT model was 22% lower than actual value; while the GT-SVM model predicted the flow volume during the training stage 1.94% higher than the actual value. As a result, the GT-SVM model provided a more accurate estimation from the flow volume during the training stage than the SWAT model.

Figure 12 illustrates the observed and predicted cumulative runoff curve by the SWAT and GT-SVM models during the testing (validation) period. The total observed discharge volume during the testing stage was equal to 375.34 m^3/s. The GT-SVM and SWAT models predicted this value as 420.18 m^3/s and 354.604 m^3/s, respectively. The predicted flow volume using the SWAT model was 5.5% lower than actual value; while the GT-SVM model predicted the flow volume during the testing stage 11.95% higher than the actual value. As a result, the SWAT model has provided a more accurate estimation from the flow volume during the testing stage than GT-SVM model. In summary, GT-SVM has better indices, such as RMSE and NS,

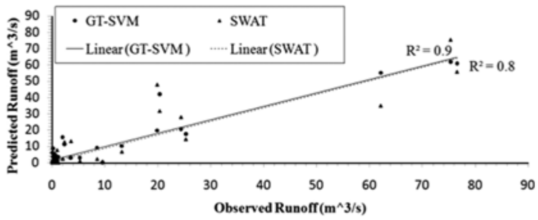

Fig. 11. Scatter Plot of Observed Flow (m^3/s) versus SWAT Data (Green Circles) and GT-SVM Data (Blue Circle)

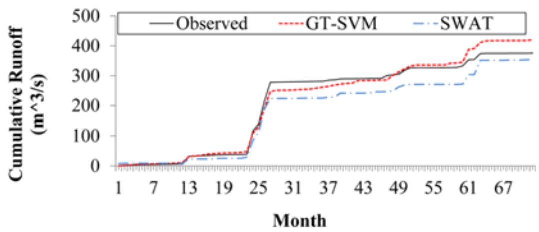

Fig. 12. Observed Cumulative and Predicted Cumulative Runoff in the Validation (Testing) Stage for Validation

Table 7. Statistical Indices of Observed and Predicted Runoff by SWAT and GT-SVM Models

	Model	n	Range	x_{max}	x_{min}	$\bar{x}$	$x_{max}/\bar{x}$	σ^2
Observed Runoff	---	72	72.554	76.581	0.02652	5.213	14.69	224.02
Predicted Runoff	SWAT	72	75.65	75.65	0	4.93	15.35	185.35
	SVM	72	61.79	61.83	0.04	5.84	10.59	193.39

for the training period in comparison with the SWAT model; however, the SWAT model has a better estimation for the total predicted flow in the testing period (total flow volume).

The observed and predicted flows were evaluated over the modeling period (1990-2008). This was done by drawing a box plot to show the five significant statistics values – minimum flow, maximum flow, median flow (50th percentile), first quartile flow (25th percentile), and third quartile flow (75th percentile). A box plot is useful for displaying the distribution of a scale variable and pinpointing outliers. In this study, the resultant box plot is as depicted in Figs. 13, 14, and 15 for the SWAT and GT-SVM models.

The line that divides the box plot into two is the median; the two lines drawn at the top and bottom parts depict the maximum and minimum flow; the circle point is the relative outliers and the star is the outlier's data. In Figs. 13, 14 and 15, the box plots show that the maximum flow was in the 38th month for the observed GT-SVM and SWAT data (February-1993). The flows were also particularly high in the 36th and 75th month over the modeling period. According to the 25th percentile (first quartile) box plot, GT-SVM has an overestimation; meanwhile SWAT has an underestimated prediction of flows. Moreover, the evaluations of box plots show that SWAT underestimated the flows under the

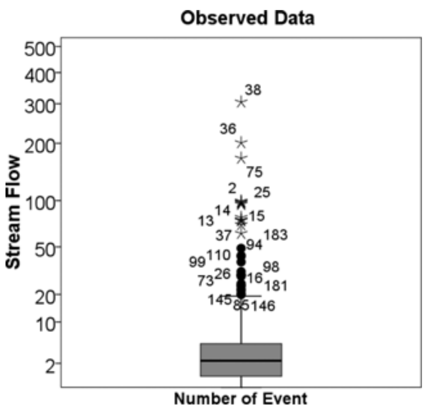

Fig. 13. Box Plot of Observed Streamflow (m^3/s) in Attributed Month (Number of event) over Modeling Period (1990-2008)

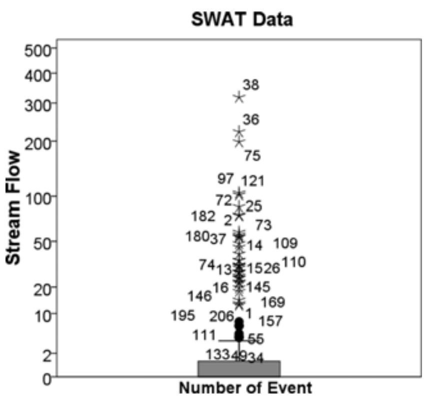

Fig. 14. Box Plot of Predicted Streamflow (m^3/s) via SWAT in Attributed Month (Number of event) over Modeling Period (1990-2008)

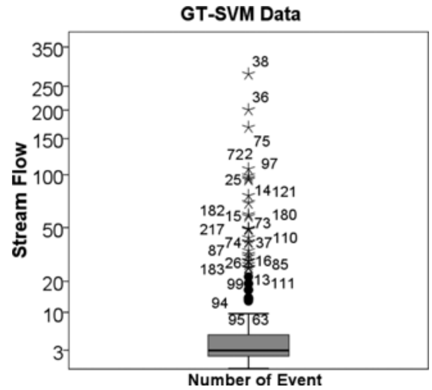

Fig. 15. Box Plot of Predicted Streamflow (m^3/s) via GT-SVM in Attributed Month (Number of event) over Modeling Period (1990-2008)

50th percentile (median) during the modeling period. On the other hand, GT-SVM has predicted flows with more agreement against observed data under the 50th percentile. As it can be seen from the box plots, GT-SVM has an overestimation for the 75th percentile (third quartile); however, SWAT has underestimated the predicted flow. Generally, distribution of low flows (around zero) indicates that GT-SVM has better predictions in comparison with SWAT. The reason can be attributed with mathematical approximation via GT-SVM.

4. Conclusions

In this study, an SVM model and a semi-distributed SWAT model was used to predict the monthly streamflow of Roodan watershed located in the southern part of Iran. In order to predict using the SVM model, the best combination of the input variables was identified using the gamma test technique (GT-SVM). Moreover, in order to assess the capability of the gamma test in determining the best combination of the input variables, the best combination was determined through the regression method between the input and output variables (Reg-SVM). The performance of the GT-SVM and Reg-SVM models was compared against each other. Then, the performance of the GT-SVM model was compared with the performance of the LLR model as a benchmark model. In addition, after preparing the required data, such as DEM, land use, and soil maps, the SWAT model was calibrated by using the SUFI-2 algorithm as a semi auto-calibration procedure.

According to the results of the gamma test, the combination of rainfall, runoff, and temperature with one time delay; rainfall and runoff with two time delays; and temperature with three time delays (R_{t-1}, Q_{t-1}, T_{t-1}, R_{t-2}, Q_{t-2}, T_{t-3}) was the best combination to predict the flow during the studied duration for Roodan watershed. The results showed that if the inputs of the model are selected using the gamma test method, they would have the lowest error in comparison to selecting them through the correlation method in predicting the flow of the area. In addition, in the training and testing phases, the GT-SVM model had better performance than the LLR model with the lowest RMSE and highest NS-coefficients value.

This study showed that both SWAT and GT-SVM models possessed a satisfying capability in predicting the monthly streamflow in Roodan watershed and there are small differences in such cases between them. For example, during calibration, GT-SVM was more satisfying by NS-coefficient (0.98) and RMSE (5.47 m^3/s). During the validation period, GT-SVM and SWAT have closer values to each other in regard to the NS-coefficient; meanwhile SWAT gave a more satisfying value for RMSE (6.1 m^3/s). It should be noted that in the testing stage, the GT-SVM model performed better in predicting peak flows over 19 m^3/s due to lower relative errors. However, the results of cumulative runoff volumes showed that SWAT has a more rewarding trend in terms of runoff volume for 2003 to 2005 in comparison with GT-SVM. This study showed that application of the SUFI-2 algorithm provided a very promising result of the SWAT model, which involved many parameters of adjustment. It should be mentioned that the application of semi auto-calibration for semi-distributed models is a good task to adjust many parameters to be faster and better.

Although artificial intelligence techniques usually provide appropriate efficiency despite data shortage in a watershed, the performance of these models is highly dependent upon utilizing patterns in their training, and if an event was beyond their training scope, the performance of the model would be extremely poor at predicting the required phenomenon. Despite the GT technique showing that it had an appropriate capability in determining the optimal combination of the input variables model; it needed more studies for achieving more knowledge towards this technique to determine an appropriate combination of the input variables, as well as the duration of the test model. It also can be mentioned that GT can be used as a modern technique for pre-processing the input variables parallel with other pre-processing techniques such as the Principal Component Analysis (PCA) method, the Genetic Algorithm (GA), and more.

Acknowledgements

We appreciate the cooperation and help given by the Department of Hydraulic and Hydrology and Research Management Center (RMC) of Universiti Teknologi Malaysia; consultant engineers of Ab Rah Saz Shargh Corporation in Iran; and the Regional Water Organization, Agricultural Organization and Natural Resources Organization of the Hormozgan province, Iran.

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