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Research papers

Complementary data-intelligence model for river flow simulation

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ABSTRACT

Despite of diverse progressions in hydrological modeling techniques, the necessity of a robust, accurate, reliable, and trusted expert system for real-time stream flow prediction still exists. The intention of the present study is to establish a new complementary data-intelligence (DI) model called wavelet extreme learning machine (WA-ELM) for forecasting river flow in a semi-arid environment. The monthly river flow data for the period 1991-2010 is used to calibrate and validate the applied predictive model, developed using antecedent flow data as predictor. The prediction efficiency of the developed WA-ELM model is validated against stand-alone ELM model. The performance of the models is diagnosed using multiple statistical metrics and graphical analysis visualization. The results reveal that incorporation of data pre-processing wavelet approach with ELM model enhances the river flow predictability. In quantitative term, the root-mean-square error (*RMSE*) and mean absolute error (*MAE*) measurements are reduced by 65% and 67% using WA-ELM over ELM model, respectively. The Taylor diagram reveals much closer proximity and the Violin plot shows similar distribution of WA-ELM simulated river flow to the observed river flow compared to stand-alone ELM simulated river flow. The hybridization of wavelet decomposition method with ELM model improves the ability of ELM model to extract the required information for modeling the non-stationary and high stochastic river flow pattern. Overall, the study reveals that WA-ELM can be a reliable methodology for modeling river flow in semi-arid environment and for different regimes (i.e., low-, medium- and high-flow).

1. Introduction

A proper knowledge on possible changes in future river flow is very important for water resources planning and management, especially for the assessment of water availability, early warning of floods and droughts, planning agricultural activities and hydropower generation (Ashrafi et al., 2017; Ghorbani et al., 2016). However, reliable prediction of river flow is extremely challenging due to its complex pattern characterized by dynamic, non-linear, and chaotic disturbances as well as the inherent randomness in behavior (Ahani et al., 2018; Yaseen et al., 2017). Development of hydrological model for effective prediction of river flow in any catchment and hydro-climatic environment is a major field of research in hydrology.

The efficiency of hydrological model depends on the attributes of the modeled catchment. River flow in tropical climatic environment, for instance, are affected by the occasional, intermittent and often unpredictable monsoon rainfall, which can cause a severe variation in the pattern of river flow and make the rainfall-runoff relationship highly non-linear. On the other hand, arid and semi-arid environment experience a scarce and erratic rainfall behavior which makes the river flow extremely complex to be predicted using hydrological models. Hence, exploration of more versatile and responsive soft computing techniques for better forecasting of river flow, particularly the highly non-linear and erratic behavior of river flow in arid environment is vital.

The river flow models can be classified broadly into two groups, the physically-based models which are developed on the basis of physical properties of catchment and the conceptual models which are mostly based on data driven techniques. The physically-based models require numerous details information of the catchment characteristics and several hydrological parameters (Sharafati and Zahabiyoun, 2014). The conceptual models, on the contrary, focuses on the use of historical input data to establish the non-linear relationships that exist between the predictor's variables and the simulated values without necessarily having a detail knowledge of the flow kinetics. Another value of these models is that they need a smaller number of hydrological inputs. Data intelligence (DI) techniques are often used for the development of conceptual models and therefore they are referred as DI models (Yaseen

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Table 1
A brief review of the application of ELM and its developed versions in modeling river flow.

Hydrological process	Reference	Application type	Predictive model	Variables (input/output)	Study location	Time scale
River flow forecasting	Siqueira et al. (2014)	Univariate	ELM	River flow/river flow	Brazil	Seasonal
	Li and Cheng (2014)	Univariate	ELM, SVR	River flow/river flow	China	Monthly
	Taormina et al. (2015)	Multivariate	ELM-BCSO	Geographical information, snow, rainfall, temperature, snow depth/river flow	United state	Daily
	Atiquzzaman and Kandasamy (2015)	Univariate	ELM, EC-SVR	River flow/river flow	United state	Daily
	Lima et al. (2016)	Univariate	OSELM, MLR	River flow/river flow	Canada	Daily, monthly and yearly
	Yadav et al. (2016)	Univariate	OSELM, ANN, SVR, GP	River flow/river flow	Germany	Hourly
	Yaseen et al. (2016b)	Univariate	ELM, SVR, GRNN	River flow/river flow	Iraq	Monthly
	Rezaie-Balf and Kisi (2017)	Univariate	OP-ELM, ANN, EPR	River flow/river flow	Iran	Daily
	Yaseen et al., (2016a)	Univariate	ELM, ANN	River flow/river flow	Malaysia	Daily, weekly, monthly
	Nourani et al. (2017)	Univariate	ELM, LSSVM. ELM, LSSVM	River flow/river flow	United state	Daily
	Dariane and Azimi (2017)	Multivariate	GA-ELM, ELM,	Rainfall, temperature/river flow	Iran	Monthly
	Lima et al. (2017)	Univariate	OSELM, VC-OSELM	River flow/river flow	Canada	Daily
	Roushangar et al. (2017)	Multivariate	WA-ELM, I-ELM, G-ELM	Rainfall, river flow, drainage properties/ river flow	Iran	Monthly

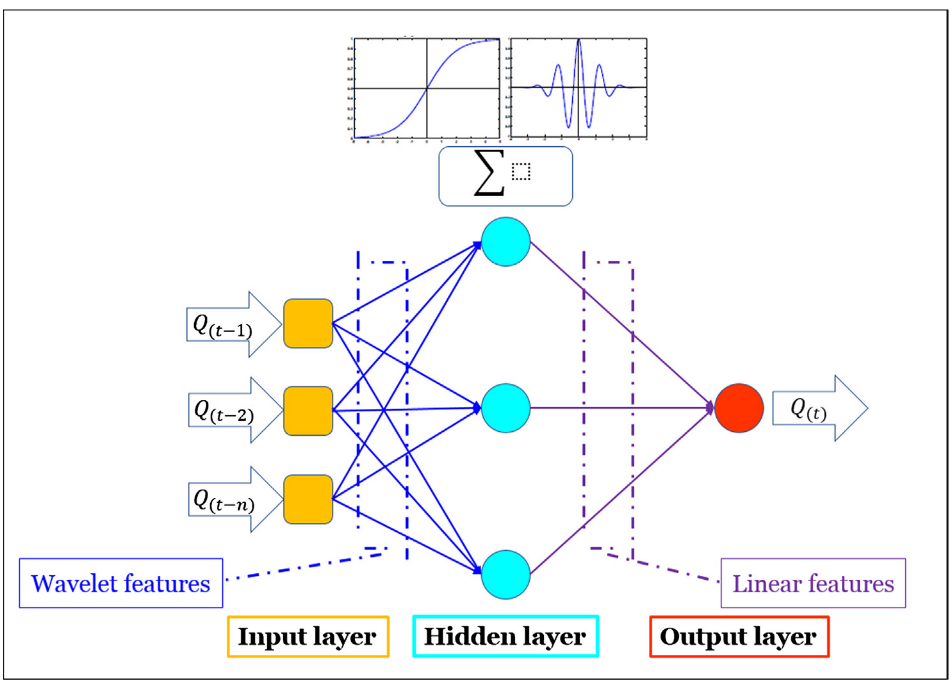

Fig. 1. The struructure of the complementary WA-ELM model.

et al., 2016).

The DI models have been developed and implemented massively in last two decades for river flow forecasting. The performance of number of DI techniques have been explored for this purpose which include artificial neural network (ANN), genetic programming, adaptive neuro-fuzzy system, support vector machine and others (Maier et al., 2014; Nourani et al., 2014a; Raghavendra and Deka, 2014; Yaseen et al., 2015). In recent years, a new version of ANN called extreme learning machine (ELM) has been introduced for the development of univariate (river flow data with different time lags are used as predictors) and multivariate (multiple hydrological variables are used as predictors) forecasting models. A brief review of the application of ELM in river flow modeling is given in Table 1. The table clearly shows a substantial progress in river flow forecasting using ELM (Atiquzzaman and Kandasamy, 2015; Li and Cheng, 2014; Lima et al., 2017, 2016; Nourani et al., 2017; Rezaie-Balf and Kisi, 2017; Roushangar et al., 2017; Siqueira et al., 2014; Taormina et al., 2015; Yadav et al., 2016; Yaseen et al., 2016b, 2016a). With other hydrological applications, ELM model evidenced its capability to simulate the nonlinear pattern (Alizamir et al., 2017; Aybar-Ruiz et al., 2016; Ebtehaj and Bonakdari, 2016; Sanikhani et al., 2018; Yaseen et al., 2018). A major drawback of ELM has been pointed out in previous studies is random initialization of the internal hidden layer weights that essentially influence the performance of ELM model. Incorporation of more reliable features as attributes can be used to overcome the drawback and improve the performance of ELM model.

Wavelet decomposition of time series data is an excellent approach for analysis of data in time and frequency domains. It provides a suitable temporal pre-processing method that can abstract the long- and short-term variations through the decomposition of time series data into several components. In other words, wavelet analysis splits the time series data into sequence of linear self-governing frequencies of

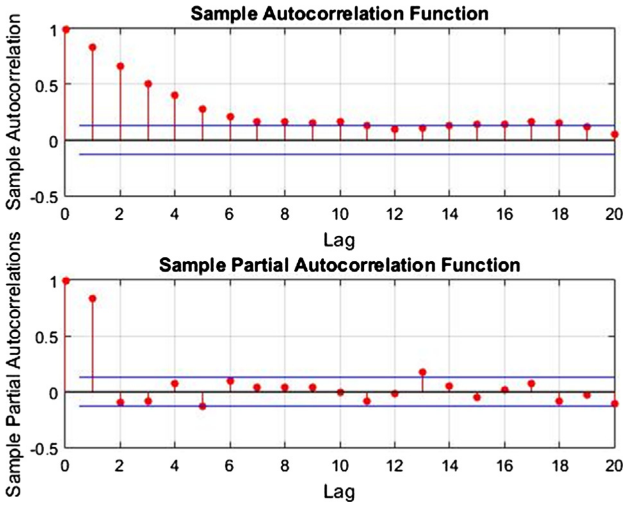

Fig. 2. The correlations of the river flow data for different time lags.

signals and approximation signal. Details of the wavelet decomposition can be found in Mallat (1989). A complementary model is a DI model integrated with data pre-processing approaches e.g., wavelet transform. The complementary models have been found to have superior ability to simulate complex hydrological processes (Nourani et al., 2014b; Yaseen et al., 2015). The wavelet approach can be used to decompose a non-stationary signal into stationary sub-signals. Hence, integration of DI models with wavelet-based data preprocessing can overcome the drawback of random initialization of the internal hidden layer weights of stand-alone ELM model and enhance the prediction capability in term of the accuracy and reliability.

The rationale behind this study is based on the fact that river flow data are inherited with significant non-stationary features presented in the form of periodic events, trends, phenomenon or other stochastic features. The wavelet approach can be used to abstract the cycle behavior of hydrological information which can be used as inputs in DI model for better prediction of river flow. The current study is an extension of the methodology proposed by Yaseen et al. (2016c) to forecast river flow using ELM model. In the present study, wavelet decomposition method is hybridized with ELM model to initiate a complementary predictive model. The performance of wavelet-ELM (WA-ELM) is investigated through the modeling river flow of Tigris river at a location in Iraq having semi-arid climate. The article is organized as follows: Section 2 presents the methodology used, followed by the description of the case study area (Section 3). Obtained results through application of complementary model in the study area are discussed in Section 4. Finally, the conclusion and remarks are drawn in the last section.

2. Methodological overview

The theoretical overview of the proposed complementary DI model, WA-ELM is presented in this section. The performance accuracy of the developed model is compared with the results obtained by Yaseen et al. (2016c) using a stand-alone ELM model.

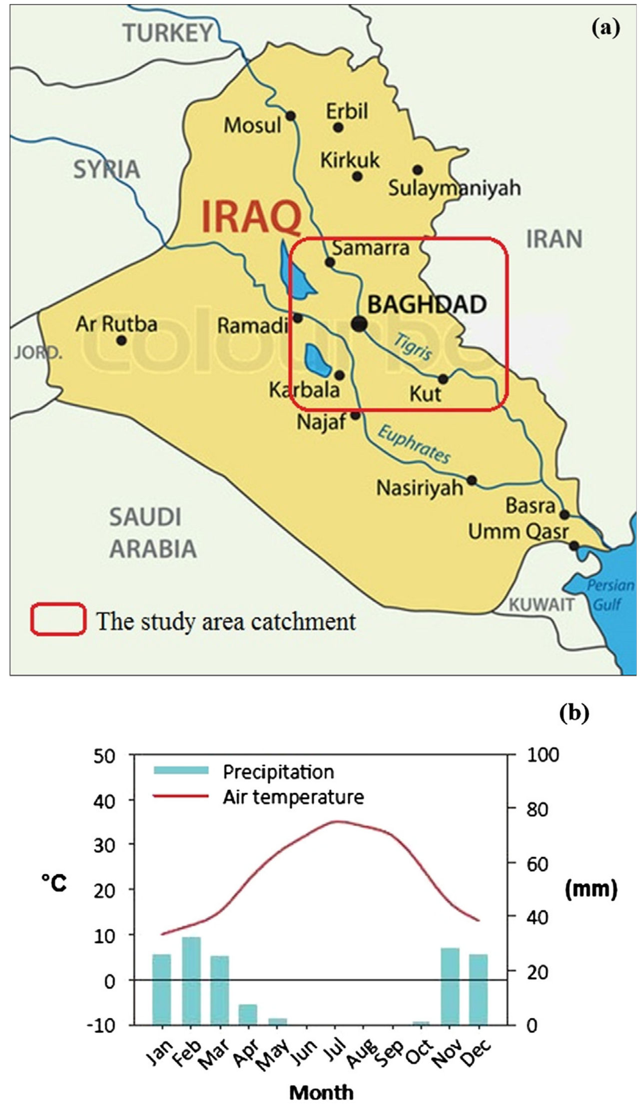

Fig. 3. (a) The location of river flow gauge station in Tigris river near Baghdad, Iraq, (b) the seasonal variation of monthly total rainfall and monthly average of daily temperature at Baghdad metrological station.

2.1. Extreme learning data-intelligence

The ELM, developed by Huang et al. (2004) is a machine learning model structured with single-layer feedforward neural network (SLFN). The main merit of this model is that the weight of the input parameters is randomly computed whereas the weights of the output parameters are analytically calculated (Yadav et al., 2017). The SLFN function integrates additives and radial basis function (RBF) hidden nodes as follows:

$$f(x) = \sum_{i=1}^{L} \beta_i G(a_i, b_i, x) \tag{1}$$

Table 2
Descriptive statistics for mean monthly stream-flow for Tigris River at Baghdad (Iraq) (1991–2010).

Partition	Time period	No. records	Q (m^3s^{-1})				
			Mean	St. Dev.	Median	Minimum	Maximum
Training	Jun. 1991 - Dec. 2007	187	780.099	379.712	674.700	298.100	2651.000
Testing	Jan. 2007 - Dec. 2010	48	489.879	136.746	445.900	331.400	936.400
Complete	Jun. 1991 - Dec. 2010	235	720.820	363.469	636.900	298.100	2651.000

Table 3
Performance assessment of the proposed WA-ELM and stand-alone ELM models during testing phase using root mean square error (*RMSE*), mean absolute error (*MAE*), Nash-Sutcliffe efficiency (*NSE*), Willmott's Index (*WI*), Legate and McCabe's Index (*LMI*), correlation coefficient (*CC*).

Models	RMSE ($m^3 s^{-1}$)	MAE ($m^3 s^{-1}$)	NSE	WI	LMI	CC
			WA-ELM			
Model 1	65.0902	45.7068	0.7687	0.9281	0.5597	0.8773
Model 2	46.0255	36.4208	0.8843	0.9994	0.6491	0.9524
Model 3[a]	30.1342	23.4216	0.9504	0.9996	0.7743	0.9762
Model 4	39.1164	28.9521	0.9164	0.9995	0.7211	0.9641
Model 5	40.8097	30.5990	0.9090	0.9995	0.7052	0.9549
			ELM			
Model 1	98.2722	87.0123	0.4727	0.8288	0.1711	0.6560
Model 2	95.5710	83.8992	0.5013	0.9985	0.0014	0.6670
Model 3	104.306	92.5438	0.4060	0.9984	0.0015	0.6645
Model 4	98.4320	85.1165	0.4710	0.9985	0.0014	0.6440
Model 5[a]	87.9055	71.5436	0.5781	0.9988	0.0011	0.6385

[a] Indicates the best input combinations in forecasting river flow.

where $f(x)$ is the output function of the ELM model; a_i and b_i are the hidden nodes learning parameters, L is the number of hidden nodes; and x is the input variable. In Eq. (1), the β_i controls the connecting weight between the output node and the *i*-th hidden node. The $G(a_i, b_i, x)$ signifies the hidden node output corresponding to input variables. The additive hidden node is solved with sigmoid activation function as follow:

$$G(a_i, b_i, x) = g(a_i.\, x + b_i) \tag{2}$$

According to Eq. (2), the weight vector that links the input layer to the *i*-th hidden-node defined by a_i and b_i, acts as the bias of the *i*-th node. The activation function $g(.)$ computes the value of $G(a_i, b_i, x)$ using RBF:

$$G(a_i, b_i, x) = g(b_i\ \|x - a_i\|) \tag{3}$$

where a_i and b_i represent the center and impact factor respectively for RBF *i*-th node. The RBF network formed by a given SLFN contains the associated RBF node in its hidden layer. The arbitrary distinct samples N are represented as (x_i, y_i) for the input and output variables. Eq. (1) can be converted to neat formula as follow:

$$H\beta = T \tag{4}$$

where, the Hussain matrix (H) of the SLFN's hidden layer output is:

$$H = \begin{bmatrix} G(a_1, b_1 + x_1) & \cdots & g_L(a_L, b_L, x_1) \\ \vdots & \ddots & \vdots \\ G(a_N.\, b_N + x_N) & \cdots & g_L(a_L, b_L, x_N) \end{bmatrix}_{NxL} \tag{5}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{Lxm} \quad \text{and,} \quad T = \begin{bmatrix} y_1^T \\ \vdots \\ y_L^T \end{bmatrix}_{Nxm} \tag{6}$$

As stated by Huang et al. (2006), the ELM model can be trained in the form of SLFN with L distinct samples that can result zero learning error. In addition, the ELM can assign random parameters to the hidden nodes even when there is less number of hidden neurons (L) compared to the number of distinct samples (N). Furthermore, it can determine the weights of the output through a pseudo-inverse of H, thereby, giving room to a small margin of error $\varepsilon > 0$. During the training period, the parameters of the hidden nodes usually assigned with random values.

2.2. Pre-processing of time series through wavelet decomposition

Time series decomposition is one of the solution for highly stochastic data that comprises of redundancy. The wavelet transform is the foundation of mathematical expression of time series frequency and signal decomposition to several components (Nourani et al., 2014b). The approach is similar to Fourier transform. However, the advantage of wavelet transformation is that it allows the components of a non-stationary signal to be analyzed which is not possible using Fourier transformation (Labat, 2005; Sifuzzaman et al., 2009). Therefore, wavelet decomposition can be used to find the necessary information required for modeling complex time series (Wei et al., 2013). Worth to mention that it is suitable for data analysis techniques with a frequency and time domain because it can decode both non-periodic and transit signals to extract information (Sifuzzaman et al., 2009). Therefore, the time series decomposition approaches have received a vast interest and successful implementation over the past decade for engineering applications and hydrology in particular (Adamowski and Chan, 2011; Nourani et al., 2017; Özger, 2010; Partal and Kişi, 2007). Time scale signals pre-processing can be defined as $f(t)$ for the continuous wavelet transform (CWT) and expressed as follows:

$$W_f(a, b, \psi) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{6}$$

Note that W_f presents the mother wavelet function and the complex conjugate phase is defined as ψ^*. The notation t denotes the time variable whereas b is the time shifting parameter. The discrete wavelet transforms (DWT) can be determined by discretizing equation:

$$W_f = a_o^{-m/2} \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\psi^*(a_o^{-m/2}t - nb_o)dt \tag{6}$$

where a_o is a fixed dilation step and b_o is the translation factor, where a and b can be determined as ($a = a_0^m$, $b = na_0^m b_0$) in the condition of a_0 greater than one; n and m are the integer unites that control the translation process.

2.3. Model development

The wavelet transformation is used to decompose the time series data of river flow into individual components which are then used as input matrix attribute for ELM model. Fig. 1 illustrates the structure of the proposed WA-ELM predictive model where the input (independent variables) and output (dependent variable) are clearly indicated. The correlated five antecedent month flow data are used to simulate river flow one-month-ahead (see Fig. 2).

The functionality of the targeted one-month ahead prediction in accordance to various input combinations starting from one to five months lag-times are presented in the following formulas:

$$\text{Model 1}: Q_{(t)} = f[Q_{(t-1)}] \tag{9}$$

$$\textit{Model 2}: Q_{(t)} = f[Q_{(t-1)}, Q_{(t-2)}] \tag{10}$$

$$\textit{Model 3}: Q_{(t)} = f[Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)}] \tag{11}$$

$$\textit{Model 4}: Q_{(t)} = f[Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)}, Q_{(t-4)}] \tag{12}$$

$$\textit{Model 5}: Q_{(t)} = f[Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)}, Q_{(t-4)}, Q_{(t-5)}] \tag{13}$$

where $Q_{(t)}$ is the forecasted value of river flow and $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$, $Q_{(t-4)}$, and $Q_{(t-5)}$ are the antecedent values of the river flow from one to five months. The performance of all the models (Eqs. (9)-(13)) are tested to select the most suitable set of antecedent river flow values as predictors to forecast the targeted flow, $Q_{(t)}$ using the proposed complementary and classical data-intelligence models. Table 2 shows the statistical summary of river flow data used in this study for training and testing of the models. Eighty percent of river flow data (16 years) are used to train the model and the rest four years data are used for testing based on the finding of previous studies used classical ELM model (Yaseen et al. 2016c).

The performance of the models is examined using a number skill assessment metrices such as root mean square error (*RMSE*), mean absolute error (*MAE*), Nash-Sutcliffe coefficient (*NSE*), Willmott's Index

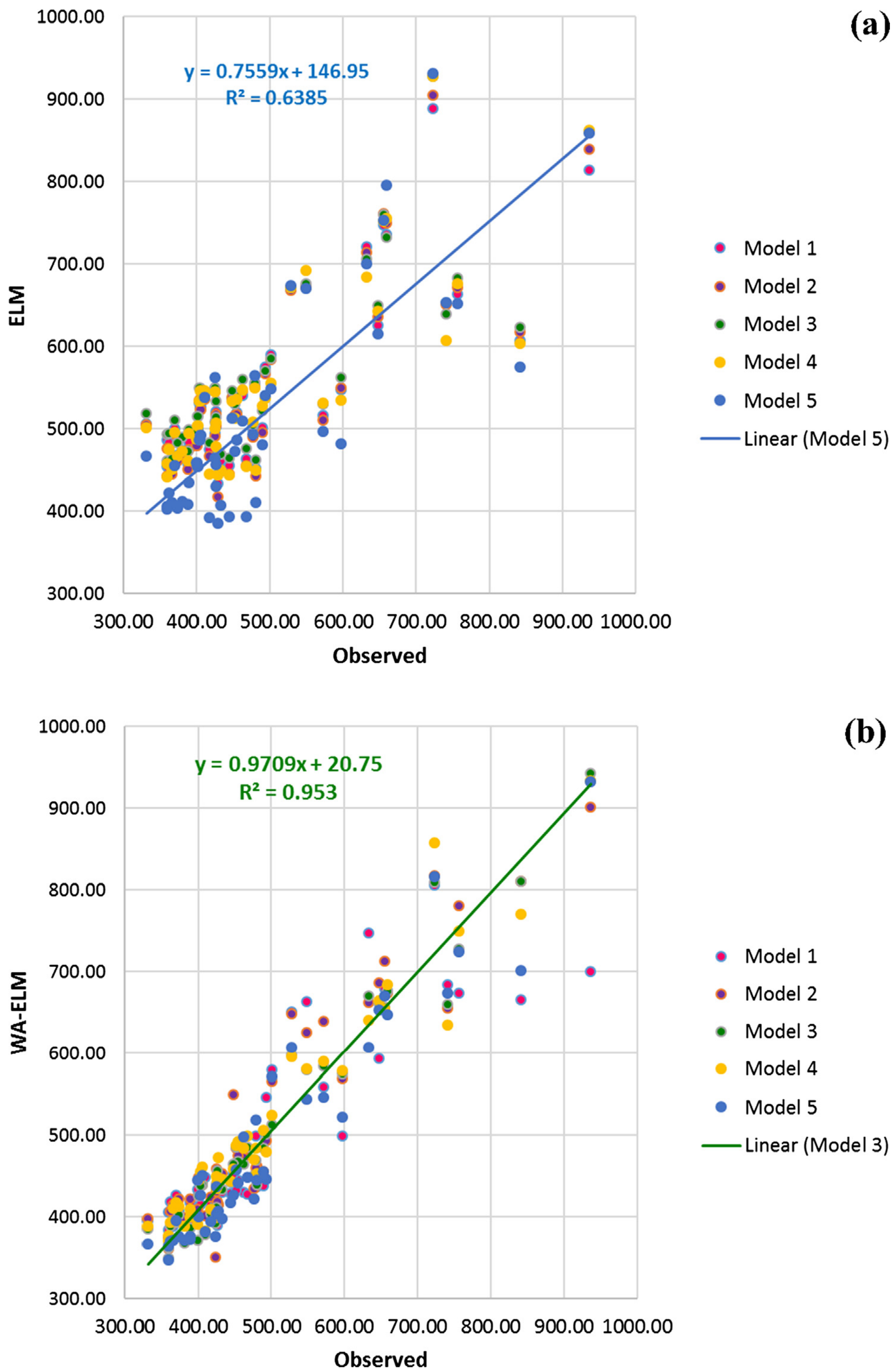

Fig. 4. Scatter plots of the observed and predicted river flow $m^3\ s^{-1}$ during testing period of (a) ELM and (b) WA-ELM models.

(*WI*), Legate and McCabe's Index (*LMI*), Correlation Coefficient and relative error (*RE*) (Tao et al., 2018a, 2018b). The formulations of the metrics are:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{n}(Q_o - Q_f)^2} \tag{14}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{n}|Q_o - Q_f| \tag{15}$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{N}(Q_o - Q_f)^2}{\sum_{i=1}^{N}(Q_o - \bar{Q}_o)^2}\right] \tag{16}$$

$$WI = 1 - \left[\frac{\sum_{i=1}^{N}(Q_o - Q_f)^2}{\sum_{i=1}^{N}(|Q_f - \bar{Q}_o| + |Q_o - \bar{Q}_o|)^2}\right] \tag{17}$$

$$LMI = 1 - \left[\frac{\sum_{i=1}^{N}|Q_o - Q_f|}{\sum_{i=1}^{N}|Q_o - \bar{Q}_o|}\right] \tag{18}$$

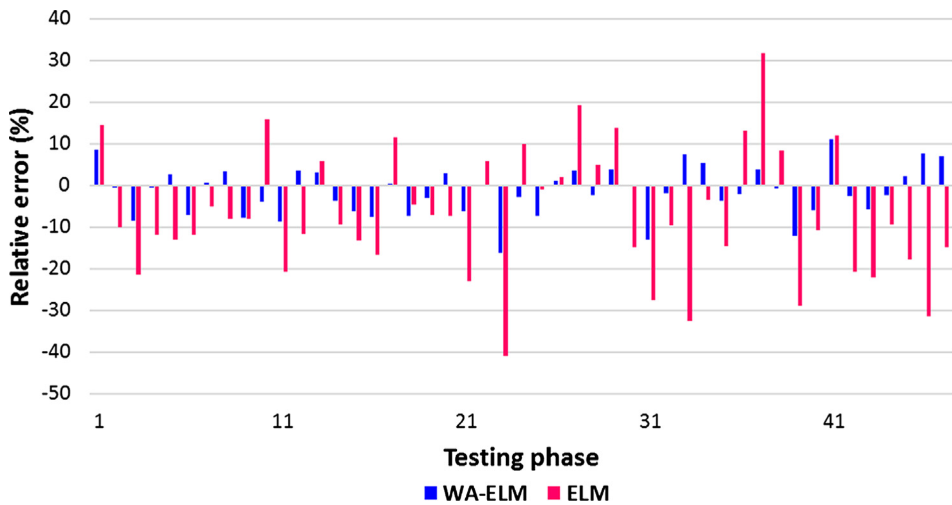

Fig. 5. The relative error (%) distribution during testing of the complementary (WA-ELM) and classical (ELM) models.

$$CC = \frac{\sum_{i=1}^{N} (Q_o - \bar{Q_o})(Q_f - \bar{Q_f})}{\sqrt{\sum_{i=1}^{N} (Q_o - \bar{Q_o})^2 \sum_{i=1}^{N} (Q_f - \bar{Q_f})^2}} \tag{19}$$

$$RE = \frac{Q_o - Q_f}{Q_o} * 100 \tag{20}$$

where the Q_o and Q_f are the observed and forecasted values of river flow; $\bar{Q_o}$ and $\bar{Q_f}$ are the mean value of the observed and forecasted values of river flow.

3. Study area and data

Tigris River is the second largest river in the Western Asia with a length of 1718 km. The river is originated in the Armenian Highlands of eastern Turkey and flows through Syria and Iraq into the Persian Gulf in Iran. The Tigris River in the map of Iraq is shown in Fig. 3a. The catchment area of Tigris river covers an area of approximately 235,000 km^2 of which over 85% is located in Iraq and hence, majority of the water resources of the river is used by Iraq. The Tigris river along with the Euphrates river is the major source of fresh water for domestic, agriculture and industrial activities of Iraq. The climate of Tigris river basin ranges from semi-humid in the north to semi-arid in the south where it meets with Euphrates River. However, arid and semi-arid climate dominates the most parts of the basin in Iraq. The average annual precipitation in the basin is approximately 300 mm, which is found vary between 150 and 800 mm in extreme wet and dry years respectively. The precipitation mostly occurs in winter (November-April), while the rest of the year is mostly dry. The daily mean temperature in the basin within Iraq goes down below 10 °C during winter and exceeds 45 °C during summer. The semi-arid to arid climatic conditions in the lowlands of Iraq and Syria cause a large loss of water through evapotranspiration in the Mesopotamian region. The mean flow of Tigris river is roughly 235 $m^3 s^{-1}$.

The monthly river flow data of Tigris river recorded at Baghdad station is used in this study to develop the complementary intelligence predictive model. Baghdad city is located in the middle part of Mesopotamian alluvial plain. In general, the soil at the studied site are driven from the nearby areas of the Mesopotamian plain and the desert in the form of residuals (sedimentation) (Turki and Noori, 2013). In addition, the soils of the site strata are affected by the changes in river course which converts the soil as coarse silt deposits over time. Hence, the site strata are erratic and non-homogenous along which the groundwater table varies with season (Mohammad Salah et al., 2012). The seasonal variations in monthly total precipitation and monthly mean of daily temperature at Baghdad meteorological station is shown in Fig. 3b.

4. Results and discussion

In this study, the WA-ELM model is developed to forecast river flow in 1-month ahead. Prediction of monthly river flow is more useful in water resources management operations such as estimation of water availability for different uses, determination of the optimum water allocation for crops, operation of dam, maintaining minimum river flow for environmental sustainability, etc. (Yaseen et al., 2016). For instance, water permit can be provided based on the availability of water in monthly time scale and the farmer can be advised to decide suitable crops based on the allocated water or the proper decision can be made in industry on the amount of productions relying on the amount of water availability.

The quality of hydrological data can significantly influence the performance of hydrological model. Therefore, the quality of river flow data is thoroughly assessed before development of model. A number of criteria is used in this study for the assessment of the quality of river flow data such as, missing data, zero or negative data, sudden change in flow followed by prolonged increase or decrease, gradual increase in flow followed by sudden decrease, etc. Besides, time series of monthly river flow data is plotted and compared with monthly rainfall time series to reveal any abnormality in seasonal pattern or large mismatch with seasonal variation of rainfall. The river flow data used in this study is found fine in term of all the above quality control criteria.

The statistical performance metrices of the proposed complementary and classical predictive models are given in Table 3. The model performance during testing phase defines the predictive capability of the model and therefore, the results obtained during model testing are discussed in following sections. The river flow of five antecedent months are found to correlate well with forecasted month. However, the best performance of the WA-ELM model is found for up to third input combination (Eq. (11)). On the contrary, the classical ELM is found to perform best using river flow of five antecedent months (Eq. (13)). This is due to the fact that machine learning based predictive models behave differently for same set of data. Solution of complex non-linear regression problem inherited with the natural pattern of the phenomena. The complementary model was able to abstract maximum information using three antecedent values through the wavelet decomposition process.

The minimum values of *RMSE* and *MAE* are found 30.13 and 23.42 $m^3 s^{-1}$ for WA-ELM and 87.90 and 71.54 $m^3 s^{-1}$ for ELM. The *NSE*, *WI*, *LMI* and *CC* values for best fit WA-ELM model are found 0.95, 0.99, 0.77 and 0.97 / 0.57, 0.99, 0.00 and 0.63, respectively. It is worth

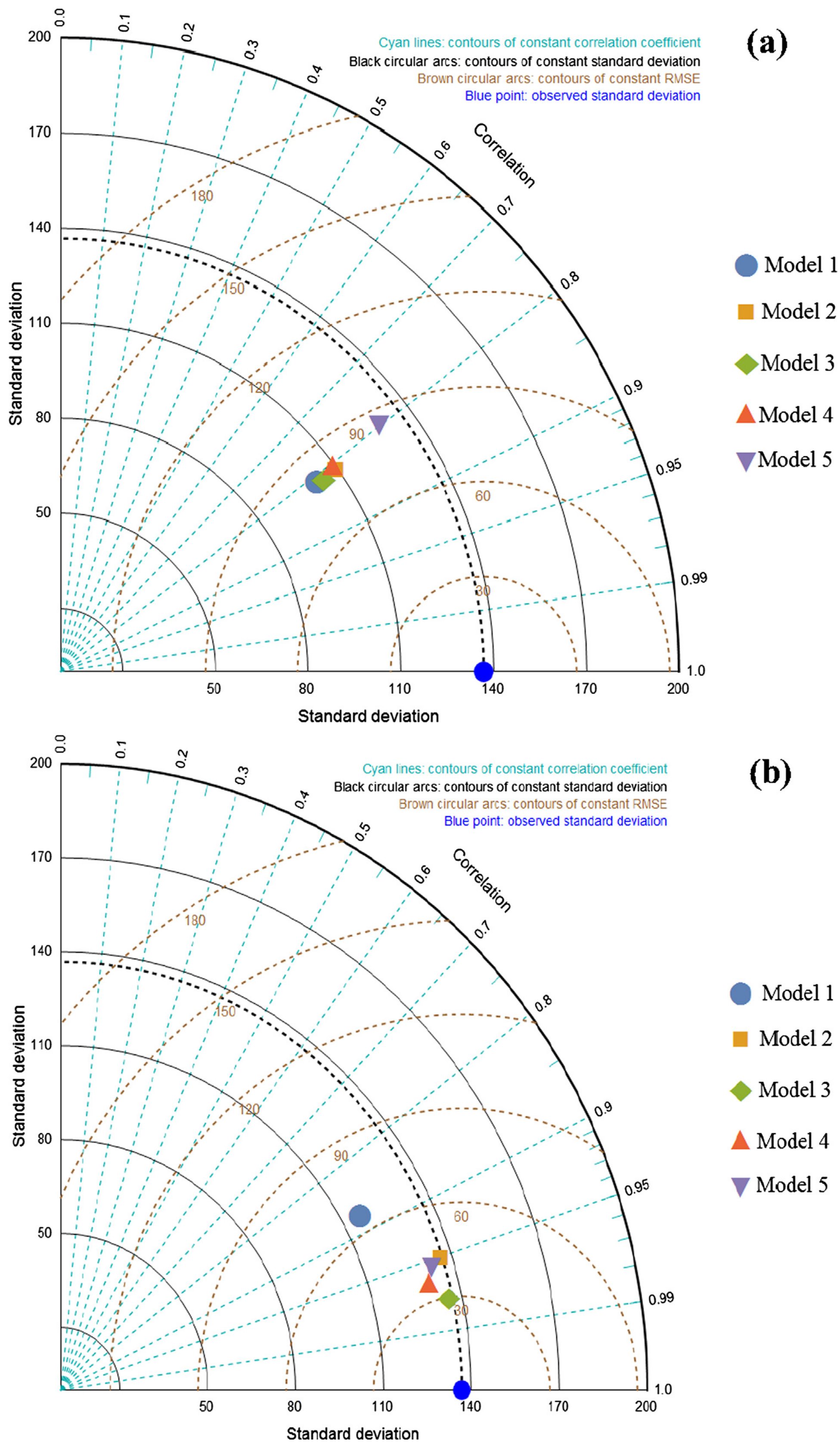

Fig. 6. Taylor diagram of the observed and simulated river flow $m^3\ s^{-1}$ for different input combinations (a) classical ELM model, (b) complementary (WA-ELM) model.

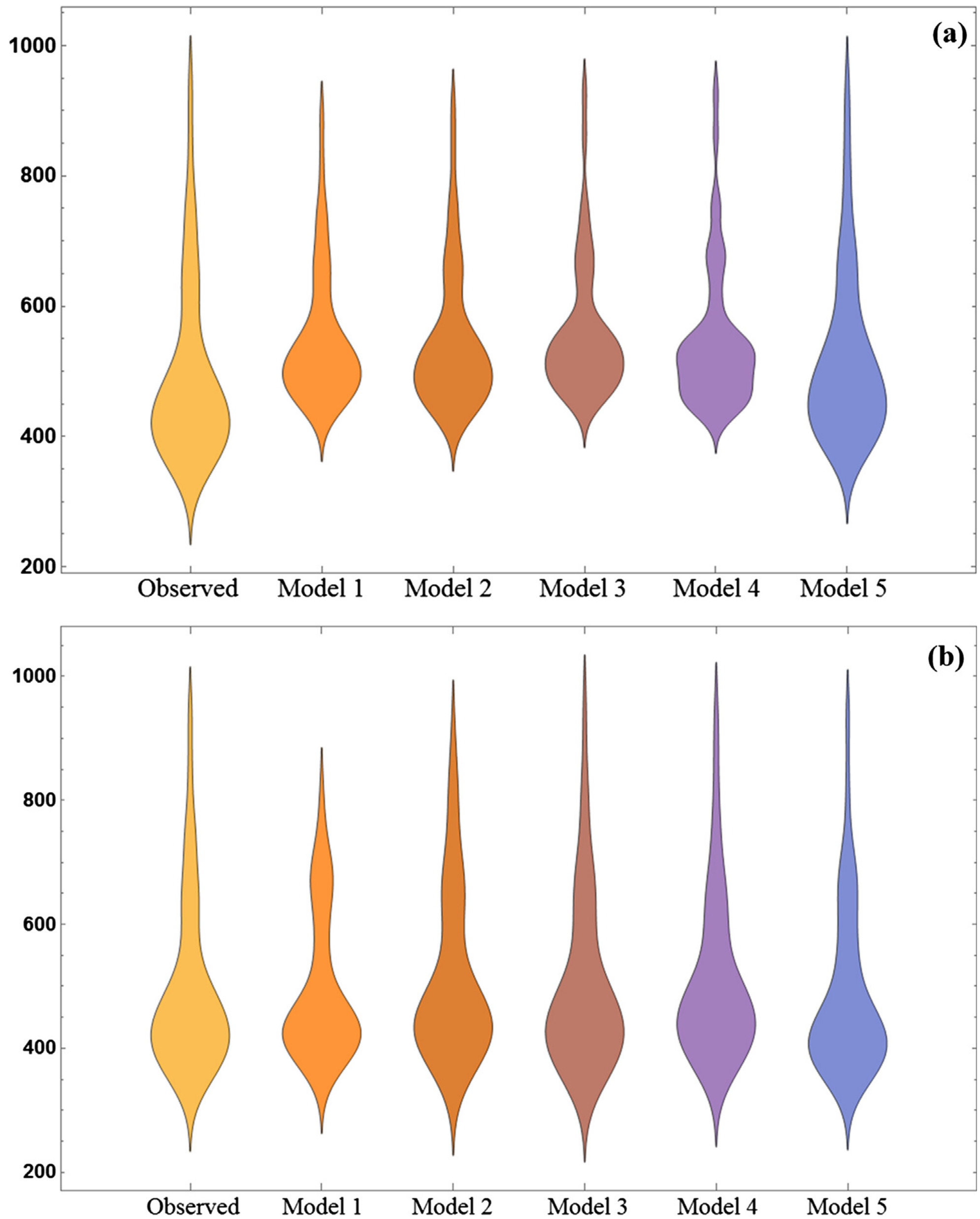

Fig. 7. Violin plots show the distribution of the observed and simulated river flow $m^3\ s^{-1}$ during model testing for different input combinations (a) classical ELM model, (b) complementary (WA-ELM) model.

to report how much augmentation in the accuracy is achieved using the proposed complementary model over the classical one. The absolute errors (*RMSE* and *MAE*) are found to reduce remarkably (65 and 67%) using the complementary model. In general, the results show a satisfactory percentage of improvement of model accuracy which can be considered significant for river flow forecasting. In addition, the attained performance accuracy proves the potential of using wavelet decomposition as input data pre-processing approach for DI models for river flow forecasting.

The observed and forecasted river flow obtained using the stand-alone ELM model with five inputs and WA-ELM model with three inputs are compared using scatter plots and presented in Fig. 4. The relationship between the modeled and the observed records are depicted in the form of least squares regression formula ($y = ax + b$), where a is a constant, y and b are used to outline the model accuracy. The R-square value represents the coefficient of determination between the observed and forecasted flow. The WA-ELM model output was found closer to the ideal line 45° compared to stand-alone ELM model output which indicates its better forecasting ability. The highest $R^2 = 0.95$ was obtained for the WA-ELM model. The scatter plot for validation period shows that the proposed WA-ELM model can capture all the three categories of river flow namely the low, medium and high flows which vary between 331.400 and 936.400 $m^3\ s^{-1}$.

The relative error (RE) distribution percentages during the testing phase give more robust and reliable measure of the predictability of the forecasting models. Fig. 5 shows the *RE* percentage during the testing period of both the WA-ELM and ELM models. The figure shows that the complementary model yields the lower magnitude of error (between ∓10% for more that 90% of the tested data) compared to ELM model (between ∓20% with some data exceeded the limit). The importance of reliable forecasting of river flow with less percentage of error is highly significant for multiple water resources engineering applications. This is particularly important for the study area as water of Tigris river is the major source of water for domestic consumption and economic activities.

The model performance using Taylor diagram (Taylor, 2001) is

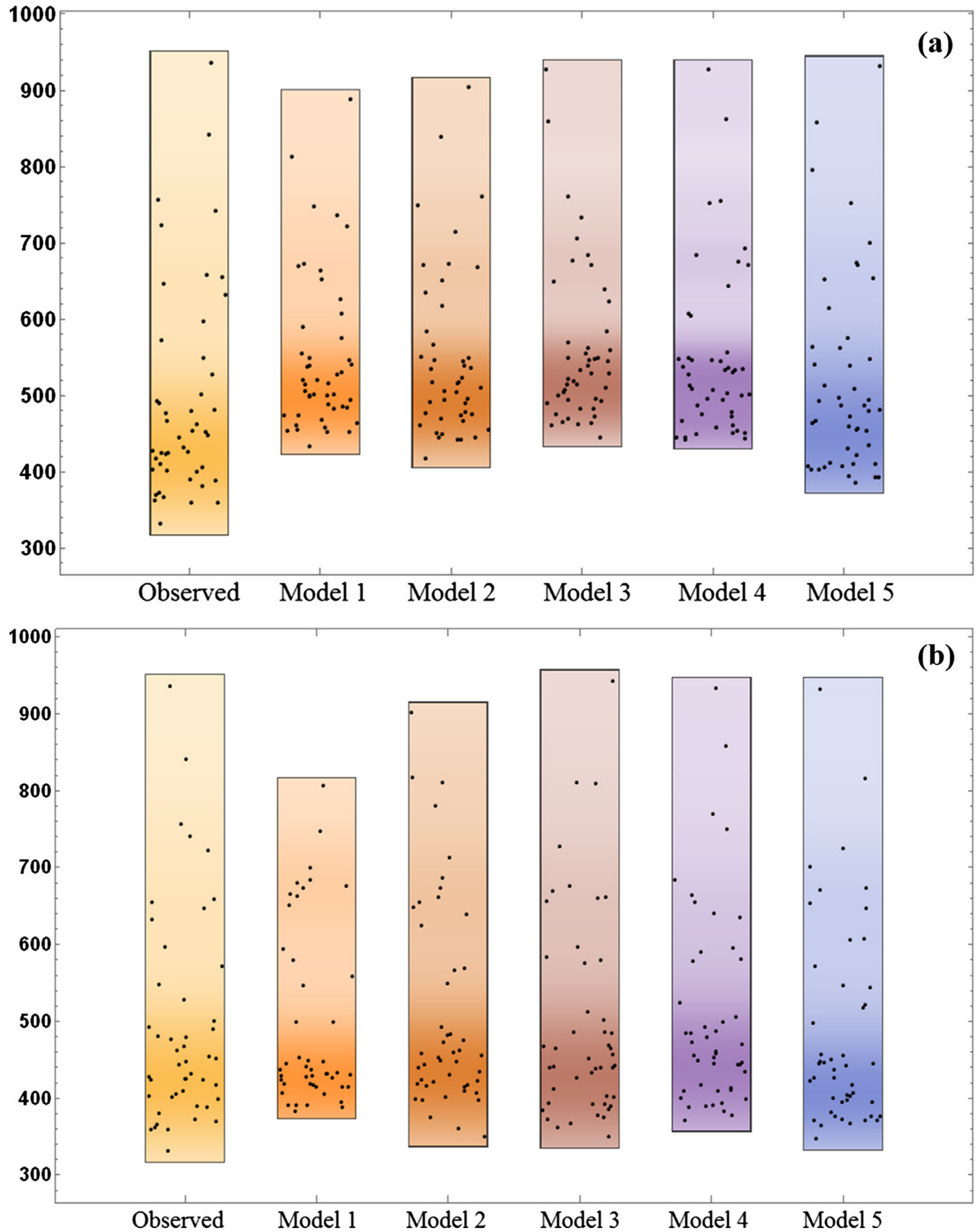

Fig. 8. Point density distribution of the observed and simulated river flow $m^3 s^{-1}$ during model testing for different input combinations (a) classical ELM model, (b) complementary (WA-ELM) model.

presented in Fig. 6. The main concept this diagram is to present the closest predictive model with the observation in two-dimensional scale (standard deviation on the polar axis and correlation coefficient on the radial axis). Taylor diagram shows that output of WA-ELM model with three antecedent day river flow is much closer to observation compared to ELM or WA-ELM models with other input combinations. The result again ascertains the better applicability of the WA-ELM model compared to classical ELM model in forecasting flow in Tigris river.

The distribution of the observed and simulated river flows obtained using both the models are presented using Violin plots (Hintze and Nelson, 1998) and point-density plots (Figs. 7 and 8). The figures show significant differences among the pair of the observed and (WA-ELM & ELM) model forecasts. However, distribution of WA-ELM simulated river flow is found much closer to observed distribution.

River flow forecasting is an essential knowledge for optimal water resources management. It is a significant step to comprehend the future events of river flow which is very important for hydropower production, irrigation management, agricultural engineering, and most imperatively for flood forecasting and mitigation. DI models have been explored to achieve this goal for more than two decades. Gradual progress has been achieved in development of reliable and robust DI models to support decision maker with accurate information. The current study is inspired by the finding of the recent review of (Nourani et al., 2014a) where the authors remarked that hybridizing DI model with decomposing time series data can enhance model accuracy remarkably compared to stand-alone DI models. ELM model considered as a very robust modern DI model that has been introduced for river flow modeling very recently. The review of recent literature revealed that highly optimistic results can be achieved using ELM model as clearly indicated in Table 1. Although the ELM has demonstrated an optimistic performance in previous studies, it suffers from a limitation due to the randomization of the initial weights of the internal tuning. In this study, wavelet transform approach is integrated with ELM to provide a complementary model called (WA-ELM). The developed model is used for forecasting river flow of Tigris River at Baghdad station, located in a semi-arid environment. Obtained results presented above undoubtedly establish the superiority of WA-ELM model over classical stand-alone ELM model. The prediction accuracy is found to increase by 65% and 67% in term of *RMSE* and *MAE* respectively, which indicates that a remarkable improvement can be achieved using complementary model.

5. Conclusion and remarks

The motivation for the current research was to investigate new complementary DI model called WA-ELM through integrating a time series pre-processing method known as wavelet transform and a DI model namely extreme learning machine for forecasting monthly flow in Tigris River at Baghdad in Iraq which have a predominantly semi-arid climate and therefore, have a very complex river flow characteristic. The architecture of the proposed model is decided based on several antecedent values identified through correlation analysis of the river flow data for different time lags. The performance of the WA-ELM model is validated against the classical ELM model developed for the same location by Yaseen et al. (2016c). The performance of the models is evaluated using several numerical and graphical prediction skill indicators. In general, the results demonstrate enhanced forecasting ability of WA-ELM. In addition, the proposed model is found capable in forecasting monthly river flow with significant reliability in a semi-arid environment. It is found that DI model behaves differently in term of optimal input attributes. The WA-ELM showed the best results with consecutive three months antecedent river flow data as predictors, whereas the stand-alone ELM is found to perform best with continuous five months antecedent data as predictors. The possibility of further improvement of WA-ELM model can be explored in future through incorporation of more casual hydrological variables such as rainfall, humidity and temperature. The current study validated the performance of the proposed model in forecasting monthly river flow. In future, the performance of the model in prediction of river flow for shorter time scale such as daily or hourly river flow can be explored.

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