Water Supply

Water Supply Vol 22 No 1, 360 doi: 10.2166/ws.2021.267

Integrating IHACRES with a data-driven model to investigate the possibility of improving monthly flow estimates

Parisa Fattahi, Afshin Ashrafzadeh *, Nader Pirmoradian and Majid Vazifedoust

Department of Water Engineering, Faculty of Agricultural Sciences, University of Guilan, 41996-13776, Khalij-e-Fars Blvd., Rasht, Iran
*Corresponding author. E-mail: ashrafzadeh@guilan.ac.ir

AA, 0000-0002-9417-6431; NP, 0000-0002-2311-5703; MV, 0000-0002-0962-2813

ABSTRACT

Estimating the outflow of basins is a critical step in surface water resources planning and management, especially in basins that lack reliable long-term observed data of streamflow. Hydrological models, which can simulate the process of rainfall-runoff, can be used to obtain reliable estimates of streamflow from precipitation data and the physical characteristics of basins. The focus of the present study was to estimate the outflow of 19 sub-basins located in Guilan Province, northern Iran. To achieve this, hybrid models were developed by integrating the IHACRES (identification of unit hydrograph and component flows from rainfall, evapotranspiration, and streamflow) hydrological model with the intelligent-based GMDH (group method of data handling) model. The IHACRES model was calibrated using monthly ground-based precipitation and temperature data as well as satellite-based precipitation data. The lowest and highest Nash-Sutcliffe coefficient (NS) for the IHACRES models were, respectively, 0.14 and 0.68 in the calibration phase and 0.11 and 0.73 in the validation phase. It was also observed that using satellite-based precipitation data reduces NS by 10–75% in the 19 sub-basins under study. After calibrating and validating the IHACRES models, the hybrid models were developed by integrating IHACRES and GMDH models. The lowest and highest NS for the hybrid models were, respectively, 0.23 and 0.81 in the calibration phase and 0.11 and 0.81 in the validation phase. It was observed that, on average, integrating IHACRES and GMDH increases the NS by 44.1% in the calibration phase and 37.0% in the validation phase in comparison with the IHACRES model. According to the NS, the hybrid model had 'acceptable' performance in six sub-basins in which the IHCRES model had 'unacceptable' performance. It was observed that integrating the IHACRES model with a data-driven model (the GMDH model) can generally improve the simulation results in all sub-basins under study.

Key words: conceptual model, hybrid model, satellite precipitation data

HIGHLIGHTS

- The IHACRES model was calibrated in 19 sub-basins located in Northern Iran.
- The GMDH model was used to improve the performance of the IHACRES model.
- Hybrid conceptual data-based models were developed by integrating IHACRES and GMDH.

1. INTRODUCTION

Accurately measured data and reliable estimates of basin yield are one of the most critical tools in water resources management. However, many basins in Iran lack suitable long-term data on runoff due to various limitations (Salehpoor Laghani *et al.* 2018). Rainfall-runoff models have always attracted the interest of hydrologists because they are a tool that can be used to simulate basin behavior in response to precipitation to obtain reliable estimates of basin output. In recent decades, various models with different perspectives in simulating the rainfall-runoff process have been developed.

IHACRES (identification of unit hydrograph and component flows from rainfall, evapotranspiration, and streamflow) is one of the rainfall-runoff conceptual models developed to minimize the need for input data. It comprises two in series modules: the non-linear loss module and the linear unit hydrograph module. The model inputs (precipitation and temperature) are first converted into effective precipitation by the nonlinear module, and then the linear module produces the runoff flowing out of the basin. Many studies have been carried out worldwide using this model and have reported its acceptable performance. Goodarzi *et al.* (2013) studied the performance of the soil and water assessment tool (SWAT), simple hydrology

(SYMHID) and IHACRES models in simulating a basin in Western Iran. They reported that although SWAT performed better than IHACRES according to the statistical criteria, IHACRES was a suitable model for the studied basin because it required a smaller amount of input data while exhibiting acceptable accuracy. Khairfam *et al.* (2013) conducted a research on seven basins in Northeastern Iran and stated that the model underestimated the peak discharges. In a study on a basin in northern Iran, Dodangeh *et al.* (2017) noticed that IHACRES had weaknesses in simulating the peak discharges but it performed well in general. Vaze *et al.* (2016) used four hydrological models including IHACRES to study the impact of climate change on the hydrology of 61 catchments in Southeast Australia. They concluded that the results of the IHACRES model were more acceptable than those of the other three. The results presented by Sadeghi *et al.* (2016) and Lotfirad *et al.* (2019a, 2019b) suggested that IHACRES exhibited acceptable efficiency in estimating the runoff in the Navarood Basin in Northern Iran and the Hablehroud Basin in Central Iran. Niromandfard *et al.* (2018) used the IHACRES model to investigate the effect of climate change on the characteristics of flow in a basin in Northeastern Iran. They reported that the Nash-Sutcliffe coefficient (NS) of the model is 0.5 in the calibration phase and 0.49 in the validation phase. Ahmadi *et al.* (2019) compared IHACRES, SWAT, and artificial neural networks (ANNs) and reported that IHACRES has acceptable performance in modeling daily, monthly, and annual flows; however, their results showed that ANNs outperform IHACRES and SWAT. Choubin *et al.* (2019) calibrated and validated the IHACRES model in four gauged basins in Iran and reported that the NS of the models range between 0.57 to 0.71 in the calibration phase and 0.53 to 0.62 in the validation phase, suggesting that the performance of the model is good or satisfactory. However, based on the NS values in four pseudo ungauged basins (−0.54 to 0.39), they concluded that the IHACRES is not an appropriate choice for flow regionalization. Esmaeili-Gisavandani *et al.* (2021) calibrated four hydrological models including IHACRES in a basin in Central Iran and concluded that the IHACRES model has acceptable performance in the calibration phase. However, they reported that in the validation phase the SWAT model outperformed the other three models.

The above-mentioned studies suggest that the IHACRES model could be considered as an appropriate choice for modeling the process of rainfall-runoff, and the model can generate acceptable estimates of basins yield in different time steps with minimum input data. Accordingly, IHACRES was used to estimate the outflow of the basins located in our study area, i.e. the Talesh-Anzali Basin, Northern Iran. However, due to the factors such as the climate of the basins under study, the basins' physical characteristics and, most importantly, the quality of the data, the model's performance was worse than expected. So, the possibility of improving the IHACRES model's performance by integrating it with a data-based model and developing a hybrid conceptual data-based model was examined in the present study. Hybrid models attracted less interest in previous research, but the few studies that were conducted using them suggested that hybrid models could perform better than each one. The research by Ashrafzadeh & Rizi (2009) (a hybrid model of time series and artificial neural networks for streamflow simulation), the work by Noori & Kalin (2016) (a combined use of SWAT and an artificial neural network for estimating daily flow in a basin in Atlanta), and the study by Fathian *et al.* (2019) (a combination of time series models and artificial neural networks to estimate monthly discharge in two basins in Canada) are examples of using hybrid models. To the best of our knowledge, integrating the IHACRES and data-based models has not been reported in previous studies. The developed hybrid models in the present study could be used in flow regionalization studies to estimate the outflow of the ungauged basins in the study area (the Talesh-Anzali Basin, Northern Iran).

Data-based models, especially models based on artificial intelligence, attracted great interest in the past two decades in modeling the rainfall-runoff process (Salehpoor Laghani *et al.* 2020). These models can find the nonlinear relationships between the recorded data on precipitation and runoff, and their different forms have been studied and evaluated in various research projects. The data-based model used in the present study is group method of data handling (GMDH). This intelligent-based model was introduced by Ivakhnenko (1971) for solving multidimensional interpolation problems. It has the capability of finding complicated relationships between the inputs and outputs of nonlinear systems. Walton *et al.* (2019) assessed GMDH performance in estimating maximum two-year return period discharges using the measured data in 365 hydrometric stations in Iowa. They recommended GMDH as an acceptable model for basins without statistical data. Dodangeh *et al.* (2020) used this model to prepare maps of areas prone to floods in a basin in Northeastern Iran and stated that GMDH yielded completely acceptable results with the minimum input data. Li *et al.* (2020) also reported that the performance of this model in predicting water levels in two rivers in China was 'acceptable.' Intelligence-based models are non-parsimonious models and use many parameters for simulating complex processes such as the rainfall-runoff process. However, the level of complexity of a process can justify choosing an intelligence-based model. Among intelligence-based models, GMDH has the advantage that its best structure is selected automatically and less parameters are needed to be optimized. So, in the present study, GMDH was chosen to transfer the output of the IHACRES model to the outflow of the basins under study.

2. MATERIALS AND METHODS

2.1. The study area

Guilan is one of the northern provinces in Iran with an area of 14,711 km^2. The Talesh-Anzali Basin, which is the smallest Class II basin in Iran, is located entirely in Guilan Province except for a very small part situated in Ardabil Province. This basin, which lies between the Aras and Sefidroud Basins, is divided into two parts by the Sefidroud Basin. The northern part includes several small coastal rivers originating from the Talesh Mountains. The other part also includes rivers pouring into the Anzali Lagoon. Figure 1 shows the location of the Talesh-Anzali Basin in Iran. In the present study, 19 sub-basins were selected in the Talesh-Anzali Basin (named s1 to s19) for modeling. The altitude of the outlet points in the selected sub-basins (the locations of the gauging stations) varies from −23 to 250 m. The area, the average annual precipitation, the average annual temperature, and the average annual flow of each sub-basin are listed in Table 1.

The data set used in the present study consisted of ground-based precipitation, temperature and flow data, and satellite-based precipitation data. The precipitation and temperature data from 17 weather stations were considered for the present study. Monthly precipitation and temperature data over 15 years (2003–2017) were retrieved from the database of Iran Meteorological Organization (IMO) and Iran Water Resources Management Company (IWRMC) and were considered as

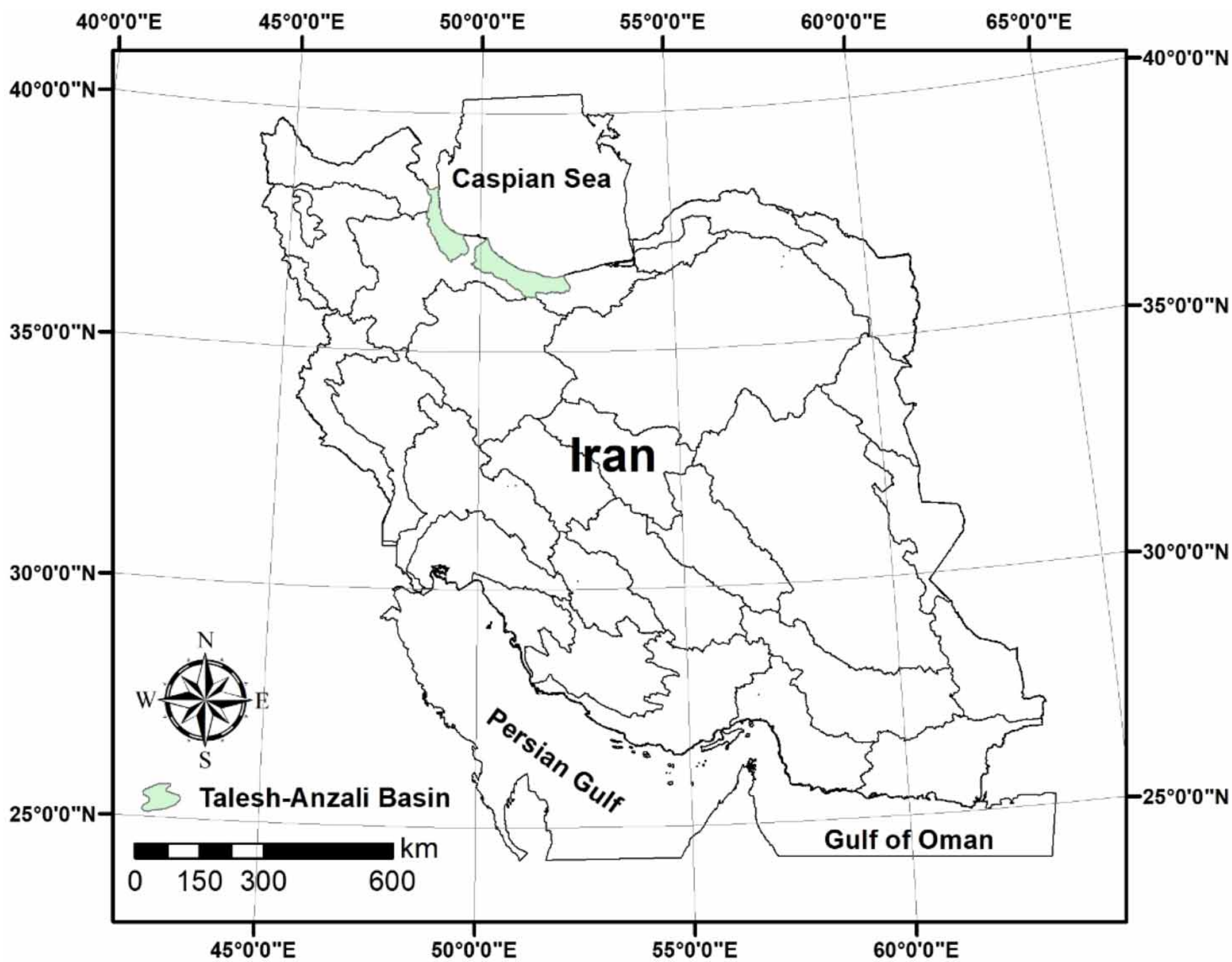

Figure 1 | Class II basins in Iran and the location of the Talesh Anzali Basin.

Table 1 | Characteristics of the sub-basins under study

Sub-basin	Area (km^2)	Average annual temperature (°C)	Average annual precipitation (mm)	Average annual flow (cms)
s1	235.2	11.8	891.4	2.2
s2	450.0	17.2	1,391.2	7.6
s3	150.0	16.5	1,481.8	5.6
s4	380.6	16.8	1,397.5	7.7
s5	47.1	12.6	933.9	1.4
s6	481.0	15.9	1,797.1	11.2
s7	115.0	12.7	1,393.4	2.3
s8	101.0	13.1	1,175.3	2.6
s9	82.4	14.9	1,384.5	1.9
s10	123.0	14.7	1,362.2	4.6
s11	345.5	14.2	1,306.6	5.6
s12	75.0	11.3	977.3	2.6
s13	63.6	13.4	1,213.2	2.3
s14	125.7	14.3	1,311.1	3.9
s15	222.0	12.3	1,093.0	4.5
s16	107.0	12.7	1,135.3	2.5
s17	285.7	15.9	1,489.1	3.7
s18	288.0	15.9	1,498.0	7.3
s19	213.6	10.8	912.8	4.7

input to the IHACRES model. Also, monthly flow data recorded in 19 gauging stations located at the end of the sub-basins under study were extracted from the database of IWRMC and were considered for the calibration and validation of the IHACRES model. The dataset was divided into calibration and validation parts, and IHACRES was calibrated over the period of 2003–2015 and validated over the period of 2015–2017. Satellite-based precipitation data including Tropical Rainfall Measuring Mission (TRMM), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), and Climate Hazards group InfraRed Precipitation with Station data (CHIRPS) datasets were also considered for the present study. Precipitation data from the three satellite-based datasets were averaged and considered as the substitute for the ground-based precipitation data and were used to calibrate the IHACRES model.

2.2. IHACRES

IHACRES is an integrated conceptual model for simulating the precipitation-runoff process at the basin scale. IHACRES is among the commonly used models because it requires a small amount of input data and is easy to use. In addition, there are suitable relationships between its parameters and the physical characteristics of the basin. This model consists of two modules, one of which is nonlinear and the other linear. The data on precipitation and temperature in the time steps of interest are first converted into effective precipitation by the nonlinear module. The effective precipitation is then converted into the flow hydrograph with the help of the linear module. Effective precipitation, u_k, is estimated as follows (Hansen *et al.* 1996):

$$u_k = \begin{cases} s_k^p r_k, & r_k > l \\ 0, & r_k \le l \end{cases} \tag{1}$$

where r_k is the observed precipitation over the time step k; p is the loss parameter; l is the precipitation threshold; and s_k (wetness index) is calculated as follows:

$$s_k = \frac{r_k}{c} + \left[1 - \frac{1}{\tau_w \exp\left[(20 - t_k)f\right]}\right] s_{k-1} \tag{2}$$

where c is the response parameter; τ_w is a time parameter for the decline in s_k; t_k is the observed temperature at the time k (°C); and f is the modulation temperature parameter. The linear module of IHACRES has two parallel components, one for quick flow, $x_k^{(q)}$, and one for slow flow, $x_k^{(s)}$ (Kim 2015). So, the streamflow at time k can be written as follows:

$$q_k = x_k^{(q)} + x_k^{(s)} \tag{3}$$

$$x_k^{(q)} = \exp\left(\frac{-\Delta}{\tau_q}\right)x_{k-1}^{(q)} + v_q\left[1 - \exp\left(\frac{-\Delta}{\tau_q}\right)\right]u_k \tag{4}$$

$$x_k^{(s)} = \exp\left(\frac{-\Delta}{\tau_s}\right)x_{k-1}^{(s)} + v_s\left[1 - \exp\left(\frac{-\Delta}{\tau_s}\right)\right]u_k \tag{5}$$

where Δ is the time step; τ_q and τ_s are, respectively, the decay time constants for the quick and slow stores; and v_q and v_s are, respectively, the relative volumetric throughputs for the quick and slow components of flow ($v_s = 1\text{-}v_q$). The linear module has only three parameters (τ_q, τ_s and v_s), making eight parameters for the model (the five parameters of the non-linear module are p, l, τ_w, c and f). The loss parameter (p) and the precipitation threshold value (l) were considered, respectively, one and zero. In the literature, one and zero are recommended for the mentioned parameters, so in the present study, the values of one and zero were considered for p and l. The optimum values of the other six parameters are determined in the calibration phase of the model through a trial and error procedure.

2.3. GMDH

GMDH was developed by Ivakhnenko (1971) to identify the complicated relationships between the inputs and outputs of nonlinear systems. In a multilayer GMDH, each layer is a combination of several processing elements, each receiving only two inputs. The output of each processing element is calculated by a polynomial as follows:

$$y = a_0 + \sum_{i=1}^{2} a_i x_i + \sum_{i=1}^{2}\sum_{j=1}^{2} a_{ij} x_i x_j \tag{6}$$

where x_i and x_j are the inputs of each processing element; and a_i and a_{ij} are the weights. The optimal values of the weights are determined in the calibration phase. During calibration, and based on an evaluation criterion, only those processing elements are kept that satisfy the evaluation criterion and the other processing elements are left out. The model is calibrated using the least square error method and based on the model output and the observed output, the processing elements that can be kept and the optimal values of the weights are determined.

In the present study, the IHACRES output (the estimated monthly flow for each sub-basin), as well as the observed flows in two previous months, was considered as the input for the GMDH model, and the observed flow for each sub-basin was estimated. The calibration and validation periods for the GMDH model were similar to those used for the IHACRES model, and the model performance was evaluated for both periods. The flowchart describing the steps of developing the hybrid models of IHACRES and GMDH is presented in Figure 2.

2.4. Error measures

The performance of the models was assessed using Root Mean Square Error (RMSE) and the Nash-Sutcliffe coefficient (NS). These measures are defined as follows (Moriasi *et al.* 2007):

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_{i(\text{obs})} - y_{i(\text{for})})^2} \tag{7}$$

$$\text{NS} = 1 - \frac{\sum_{i=1}^{m}(y_{i(\text{obs})} - y_{i(\text{for})})^2}{\sum_{i=1}^{m}(y_{i(\text{obs})} - \bar{y}_{\text{for}})^2} \tag{8}$$

where 'obs' and 'for' stands, respectively, for observed and estimated streamflows; and m is the number of all observed data.

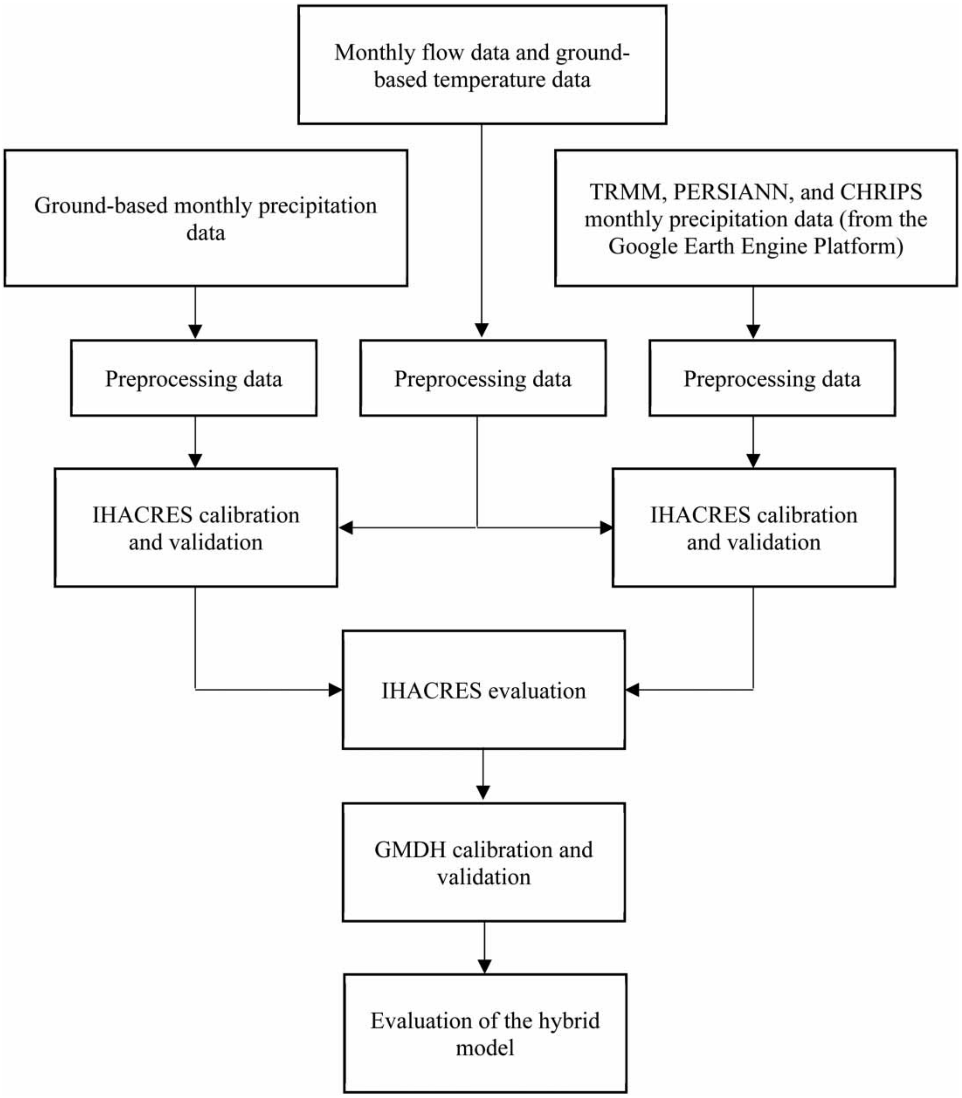

Figure 2 | Flowchart describing the steps of developing the hybrid models of IHACRES and GMDH.

3. RESULTS AND DISCUSSION

This section presents separately the calibration and validation results for the IHACRES and GMDH models. Since the GMDH model received the flows estimated by the IHACRES model as its input, its output was considered as the flows estimated by the hybrid model. The performance measures for the calibration and validation phases of the IHACRES model in each sub-basin are listed in Tables 2 and 3. As is shown in these tables, the NS for the IHACRES model ranges from 0.14 to 0.68 in the calibration phase and from 0.09 to 0.73 in the validation phase. NS values of 0.45 to 0.85 (Vaze *et al.* 2016), 0.57 to 0.71 (Choubin *et al.* 2019), and 0.61 (Ahmadi *et al.* 2019) have been reported in previous studies in the calibration phase. So, the performance of the IHACRES model in the present study was worse than expected. This might be because of the quality of the input data (rainfall and temperature) and, more importantly, the poor quality of the flow data recorded at gauging stations in the sub-basins under study. It is also worth noting that the length of the data series used for model calibration was not identical for all 19 sub-basins under study, and it was observed that the model shows better performance in the sub-basins with longer calibration data series. The NS is usually considered a basis for performance evaluation of rainfall-runoff models. If the value of this coefficient is <0.30, 0.30–0.50, 0.50–0.75, or >0.75, the performance of the model is considered, respectively, 'unacceptable,' 'acceptable,' 'good,' and 'very good.' Based on this, and considering Table 2, the performance of the model for the calibration phase in eight out of 19 sub-basins was 'unacceptable,' and the model's

Table 2 | Performance of the IHACRES model in the calibration phase (ground-based precipitation)

Sub-basin	Qualitative performance	NS[a]	RMSE[b] (cms)
s1	Unacceptable	0.28	1.31
s2	Good	0.58	2.80
s3	Unacceptable	0.19	1.34
s4	Good	0.67	1.58
s5	Unacceptable	0.14	0.63
s6	Unacceptable	0.28	2.51
s7	Unacceptable	0.14	0.95
s8	Acceptable	0.42	1.32
s9	Good	0.56	1.11
s10	Unacceptable	0.23	3.46
s11	Good	0.68	2.17
s12	Acceptable	0.42	1.40
s13	Unacceptable	0.25	1.58
s14	Good	0.51	2.39
s15	Acceptable	0.48	2.23
s16	Acceptable	0.39	1.43
s17	Good	0.67	1.71
s18	Acceptable	0.31	3.85
s19	Unacceptable	0.25	2.78

[a]The Nash-Sutcliffe coefficient.
[b]Root Mean Square Error.

Table 3 | Performance of the IHACRES model in the validation phase (ground-based precipitation)

Sub-basin	Qualitative performance	NS[a]	RMSE[b] (cms)
s1	Acceptable	0.40	0.86
s2	Very good	0.83	2.83
s3	Unacceptable	0.12	2.36
s4	Acceptable	0.48	2.17
s5	Unacceptable	0.09	1.62
s6	Unacceptable	0.23	2.58
s7	unacceptable	0.09	2.50
s8	Unacceptable	0.24	1.51
s9	Good	0.52	1.16
s10	Unacceptable	0.11	3.72
s11	Good	0.64	2.30
s12	Good	0.51	1.29
s13	Unacceptable	0.24	1.59
s14	Acceptable	0.47	2.49
s15	Acceptable	0.45	2.29
s16	Unacceptable	0.27	1.56
s17	Good	0.73	1.55
s18	Unacceptable	0.29	3.91
s19	Unacceptable	0.16	2.94

[a]The Nash-Sutcliffe coefficient.
[b]Root Mean Square Error.

performance in six sub-basins was ‘good.’ Table 3, which presents the validation results, indicates that the values of the NS in 10 sub-basins were less than 0.30 and hence the model performance in these sub-basins was ‘unacceptable.’ It is noteworthy that the values of NS for the validation period increased in some sub-basins (for example, from 0.28 to 0.40 in the s1 sub-basin and from 0.58 to 0.83 in the s2 sub-basin) so that the model performance for the validation period in these two sub-basins was ‘acceptable’ and ‘very good’, respectively.

As stated before, the focus of the present study was to investigate the possibility of improving the performance of the IHACRES model. To achieve this, we first assessed the replacement of the ground-based rainfall data in the sub-basins under study (the input to the model) by satellite-based precipitation data. The results of using the satellite-based data for precipitation in calibrating the IHACRES model are presented in Tables 4 and 5. As shown in these tables, the values of the NS for the sub-basins under study decreased by 10–75% compared to modeling in which the ground-based precipitation data were used. In all, the use of remote sensing data decreased the accuracy of modeling. Consequently, the models calibrated using the ground-based data were used in the next stage.

After calibrating and validating the IHACRES models, hybrid models were developed to improve the performance of IHACRES. The hybrid models were developed by integrating the IHACRES and GMDH models. The outputs of the IHACRES model in the studied sub-basins, as well as the observed monthly flow in two previous months, were considered as the inputs for the GMDH model. So, the hybrid models, which consist of the IHACRES and GMDH models, receive rainfall and temperature as input and generate estimates of the outflow of the sub-basins under study. Tables 6 and 7 list the results of evaluating the performance of the hybrid model in the calibration and validation phases for each sub-basin. To better compare the results, the increases in the values of the NS in the hybrid model compared to the IHACRES model for the studied sub-basins are also presented in Tables 6 and 7.

As shown in Tables 6 and 7, the combination of the IHACRES and GMDH models considerably increased the values of the NS and improved the results for the calibration and validation phases. In other words, it was shown that the hybrid model outperforms the IHACRES model. Based on the values of the NS in the validation phase, the hybrid model had ‘acceptable’ performance in six of the sub-basins in which the IHACRES model had ‘unacceptable’ performance. Moreover, the

Table 4 | Performance of the IHACRES model in the calibration phase (satellite-based precipitation)

Sub-basin	Qualitative performance	NS[a]	RMSE[b] (cms)	Change in NS (%)
s1	Unacceptable	0.25	1.34	−10.7
s2	Unacceptable	0.15	2.25	−74.1
s3	Unacceptable	0.10	3.37	−47.4
s4	Acceptable	0.41	2.03	−38.8
s5	Unacceptable	0.19	0.92	35.7
s6	Unacceptable	0.24	2.99	−14.3
s7	Unacceptable	0.21	1.40	50.0
s8	Acceptable	0.36	1.38	−14.3
s9	Acceptable	0.41	1.28	−26.8
s10	Unacceptable	0.12	3.70	−47.8
s11	Good	0.51	2.69	−25.0
s12	Unacceptable	0.27	1.57	−35.7
s13	Unacceptable	0.27	1.56	8.0
s14	Acceptable	0.39	2.67	−23.5
s15	Unacceptable	0.27	2.64	−43.8
s16	Acceptable	0.31	1.52	−20.5
s17	Acceptable	0.47	2.17	−29.9
s18	Unacceptable	0.22	4.10	−29.0
s19	Unacceptable	0.13	2.99	−48.0

[a]The Nash-Sutcliffe coefficient.
[b]Root Mean Square Error.

Table 5 | Performance of the IHACRES model in the validation phase (satellite-based precipitation)

Sub-basin	Qualitative performance	NS[a]	RMSE[b] (cms)	Change in NS (%)
s1	Acceptable	0.36	1.16	−10.0
s2	Unacceptable	0.22	1.80	−73.5
s3	Unacceptable	0.06	2.72	−50.0
s4	Unacceptable	0.29	1.45	−39.6
s5	Unacceptable	0.12	1.22	33.3
s6	Unacceptable	0.19	2.30	−17.4
s7	Unacceptable	0.13	2.30	44.4
s8	Unacceptable	0.20	1.55	−16.2
s9	Acceptable	0.36	1.34	−31.2
s10	Unacceptable	0.06	3.82	−48.6
s11	Acceptable	0.49	2.74	−23.0
s12	Acceptable	0.42	1.40	−17.6
s13	Unacceptable	0.26	1.57	9.1
s14	Acceptable	0.35	2.76	−25.1
s15	Unacceptable	0.25	2.68	−45.1
s16	Unacceptable	0.21	1.63	−21.3
s17	Acceptable	0.49	2.13	−33.2
s18	Unacceptable	0.19	4.18	−34.1
s19	Unacceptable	0.08	3.08	−47.6

[a]The Nash-Sutcliffe coefficient.
[b]Root Mean Square Error.

Table 6 | Performance of the hybrid model in the calibration phase

Sub-basin	Qualitative performance	NS[a]	RMSE[b] (cms)	Change in NS (%)
s1	Acceptable	0.44	0.72	57.1
s2	Good	0.57	2.28	−1.7
s3	Unacceptable	0.23	1.27	21.1
s4	Very good	0.81	2.6	20.9
s5	Acceptable	0.35	1.75	150.0
s6	Acceptable	0.39	3.01	39.3
s7	Acceptable	0.38	3.01	171.4
s8	Good	0.61	1.08	45.2
s9	Good	0.68	0.94	21.4
s10	Unacceptable	0.29	3.32	26.1
s11	Good	0.64	2.30	−5.9
s12	Good	0.68	1.04	61.3
s13	Acceptable	0.50	1.29	98.1
s14	Good	0.71	1.84	39.1
s15	Good	0.52	2.14	8.3
s16	Good	0.53	1.25	36.6
s17	Good	0.69	1.66	3.0
s18	Acceptable	0.38	3.65	22.6
s19	Acceptable	0.38	2.53	24.0

[a]The Nash-Sutcliffe coefficient.
[b]Root Mean Square Error.

Table 7 | Performance of the hybrid model in the validation phase

Sub-basin	Qualitative performance	NS[a]	RMSE[b] (cms)	Change in NS (%)
s1	Good	0.51	1.31	27.5
s2	Very good	0.81	3.89	−2.4
s3	unacceptable	0.11	3.08	−8.3
s4	Good	0.63	3.71	31.3
s5	Unacceptable	0.19	4.1	111.1
s6	Acceptable	0.34	2.68	47.8
s7	Unacceptable	0.25	1.24	177.8
s8	Acceptable	0.35	1.39	44.6
s9	Good	0.63	1.02	22.0
s10	Unacceptable	0.21	3.50	90.9
s11	Good	0.61	2.40	−5.4
s12	Good	0.54	1.25	5.9
s13	Acceptable	0.32	1.50	33.3
s14	good	0.66	1.99	40.6
s15	Acceptable	0.49	2.21	7.8
s16	Acceptable	0.36	1.46	32.6
s17	Very good	0.75	1.49	3.0
s18	Acceptable	0.35	3.74	20.4
s19	Acceptable	0.31	2.67	23.1

[a]The Nash-Sutcliffe coefficient.
[b]Root Mean Square Error.

performance of the hybrid model was 'very good' in two sub-basin. In all, the hybrid model improved the results in 10 out of the 19 sub-basins under study. Although the performance of the hybrid model was still 'unacceptable' in four sub-basins in the validation phase, the increase in the values of the NS compared to the IHACRES model suggests that integrating the IHACRES and GMDH models could improve the results.

4. CONCLUSION

The results of the present study showed that an integration of a conceptual hydrological model (IHACRES) and a data-based model (GMDH) could improve the performance of the hydrological model. The output of the hydrological model was used as the input of GMDH, and in other words, the data-based model was used as an optimization tool for improving the estimates generated by the IHACRES model. An advantage of the methodology used in the present study was avoiding examining different combinations of meteorological variables that are normally used as the input of data-based models. Usually, finding the optimum combination of input variables is a challenging task in developing data-based models such as GMDH. However, in the present study, this was avoided by considering the output of IHACRES as the input of GMDH, and hybrid models were developed to estimate the outflow of the basins under study. All the basins under study had identical climates and conditions; however, according to the NS, the qualitative performance of the IHACRES model varied from 'unacceptable' to 'very good.' Integrating the IHACRES and GMDH models either increased modeling accuracy in all the studied basins or, if it did not improve modeling accuracy, the qualitative performance of the model did not change as shown by the values of the NS.

ACKNOWLEDGEMENT

The authors wish to thank Iran Meteorological Organization and Guilan Regional Water Authority for providing part of the data used in this study. We should also like to thank the reviewers and the editors who have given up valuable time to review the manuscript and offer valuable comments.

FUNDING

Not applicable.

CONFLICTS OF INTEREST/COMPETING INTERESTS

The authors prefer all the potential reviewers from the authors' country are excluded from reviewing the manuscript.

AUTHORS CONTRIBUTIONS

All authors contributed to the study's conception and design. Material preparation and data collection were performed by Parisa Fattahi. Data analysis and interpreting the results were performed by Parisa Fattahi, Afshin Ashrafzadeh, Nader Pirmoradian, and Majid Vazifehdoust. The first draft of the manuscript was written by Parisa Fattahi and Afshin Ashrafzadeh, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

ETHICS APPROVAL

Not applicable

CONSENT TO PARTICIPATE

Not applicable

CONSENT FOR PUBLICATION

Not applicable

DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories. https://data.irimo.ir/http://wrs.wrm.ir/amar/login.asp

REFERENCES

Ahmadi, M., Moeini, A., Ahmadi, H., Motamedvaziri, B. & Zehtabiyan, G. R. 2019 Comparison of the performance of SWAT, IHACRES and artificial neural networks models in rainfall-runoff simulation (case study: Kan watershed, Iran). *Physics and Chemistry of the Earth* **111**, 65–77. https://doi.org/10.1016/j.pce.2019.05.002.

Ashrafzadeh, A. & Rizi, A. P. 2009 A hybrid neural network based model for synthetic time series generation. In: *Eleventh International Symposium on Water Management and Hydraulic Engineering*, Ohrid, Macedonia.

Choubin, B., Solaimani, K., Rezanezhad, F., Habibnejad Roshan, M., Malekian, A. & Shamshirband, S. 2019 Streamflow regionalization using a similarity approach in ungauged basins: application of the geo-environmental signatures in the Karkheh River Basin, Iran. *Catena* **182**, 104128. https://doi.org/10.1016/j.catena.2019.104128.

Dodangeh, E., Shahedi, K. & Soleimani, K. 2017 Application of Copula theory for IHACRES hydrologic model evaluation (Case study: Taleghan watershed). *Journal of the Earth and Space Physics* **44** (1), 71–88 (in Persian). doi:10.22059/JESPHYS.2017.206373.1006789.

Dodangeh, E., Panahi, M., Rezaie, F., Lee, S., Tien Bui, D., Lee, C. W. & Pradhan, B. 2020 Novel hybrid intelligence models for flood-susceptibility prediction: meta optimization of the GMDH and SVR models with the genetic algorithm and harmony search. *Journal of Hydrology* **590**, 125423. https://doi.org/10.1016/j.jhydrol.2020.125423.

Esmaeili-Gisavandani, H., Lotfirad, M., Soori Damirchi Sofla, M. & Ashrafzadeh, A. 2021 Improving the performance of rainfall-runoff models using the gene expression programming approach. *Water and Climate Change*. https://doi.org/10.2166/wcc.2021.064.

Fathian, F., Mehdizadeh, S., Kozekalani Sales, A. & Safari, M. J. S. 2019 Hybrid models to improve the monthly river flow prediction: integrating artificial intelligence and non-linear time series models. *Journal of Hydrology* **575**, 1200–1213. https://doi.org/10.1016/j.jhydrol.2019.06.025.

Goodarzi, M. R., Zahabiyoun, B., Massah Bavani, A. R. & Kamal, R. 2013 Performance comparison of three hydrological models SWAT, IHACRES and SIMHYD for the runoff simulation of Gharesou basin. *Water and Irrigation Management* **2** (1), 25–40 (in Persian). doi:10.22059/JWIM.2012.25090.

Hansen, D. P., Ye, W., Jakeman, A. J., Cooke, R. & Sharma, P. 1996 Analysis of the effect of rainfall and streamflow data quality and catchment dynamics on streamflow prediction using the rainfall-runoff model IHACRES. *Environmental Software* **11**, 193–202. https://doi.org/10.1016/S0266-9838(96)00048-2.

Ivakhnenko, A. 1971 Polynomial theory of complex systems. *IEEE Transactions on Systems, Man and Cybernetics* **SMC-1** (4), 364–378.

Khairfam, H., Mostafazadeh, R. & Sadeghi, H. 2013 Estimation of daily discharge using IHACRES model in some watersheds of Golestan province. *Journal of Watershed Management* **4** (7), 114–127 (in Persian).

Kim, H. S. 2015 Application of a baseflow filter for evaluating model structure suitability of the IHACRES CMD. *Journal of Hydrology* **521**, 543–555 https://doi.org/10.1016/j.jhydrol.2014.12.030.

Li, Y., Shi, H. & Liu, H. 2020 A hybrid model for river water level forecasting: cases of Xiangjiang River and Yuanjiang River, China. *Journal of Hydrology* **587**, 124934. https://doi.org/10.1016/j.jhydrol.2020.124934.

Lotfirad, M., Adib, A. & Haghighi, A. 2019a Estimation of daily runoff using IHACRES semi-conceptual model in Navroud catchment of Guilan. *Echo Hydrology* **5** (2), 449–460 (in Persian). doi:10.22059/IJE.2017.234237.614.

Lotfirad, M., Salehpoor Laghani, J. & Ashrafzadeh, A. 2019b Using the IHACRES model to investigate the impacts of changing climate on streamflow in a semi-arid basin in north-central Iran. *Journal of Hydraulic Structures* **5** (1), 27–41.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. & Veith, T. L. 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50**, 885–900. https://doi.org/10.13031/2013.23153.

Niromandfard, F., Zakerinia, M. & Yazerloo, B. 2018 Investigating the effect of climate change on river flow using IHACRES rainfall-runoff model. *Irrigation Sciences and Engineering* **41** (3), 103–117 (In Persian). doi:10.22055/JISE.2018.13750.

Noori, N. & Kalin, L. 2016 Coupling SWAT and ANN models for enhanced daily streamflow prediction. *Journal of Hydrology* **533**, 141–151. https://doi.org/10.1016/j.jhydrol.2015.11.050.

Sadeghi, H., Ghasemieh, H. & Sadati Nezhad, J. 2016 Evaluating the efficiency of IHACRES hydrological model in wetlands: a case study of Navarud basin, Guilan. *Journal of Soil and Water Sciences* **19** (73), 73–82 (in Persian).

Salehpoor Laghani, J., Ashrafzadeh, A. & Moussavi, S. A. 2018 Water resources allocation management in Hablehroud basin using a combination of the SWAT and WEAP models. *Iran-Water Resources Research* **14** (3), 278–290 (in Persian).

Salehpoor Laghani, J., Ashrafzadeh, A. & Moussavi, S. A. 2020 Investigating the uncertainty of data-based models in forecasting monthly flow of the Hablehroud River. *Iranian Journal of Soil and Water Research* **51** (5), 1265–1280 (in Persian). doi:10.22059/IJSWR.2020.286920.668288.

Vaze, J., Post, D. A., Chiew, F. H., Perraud, J. M., Viney, N. & Teng, J. 2016 Climate non-stationarity-validity of calibrated precipitation-runoff models for use in climate change studies. *Journal of Hydrology* **394** (3–4), 447–457. https://doi.org/10.1016/j.jhydrol.2010.09.018.

Walton, R., Binns, A., Bonakdari, H., Ebtehaj, I. & Gharabaghi, B. 2019 Estimating 2-year flood flows using the generalized structure of the Group Method of Data Handling. *Journal of Hydrology* **575**, 671–689. https://doi.org/10.1016/j.jhydrol.2019.05.068.

First received 12 May 2021; accepted in revised form 8 August 2021. Available online 19 August 2021