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Quantifying Diyala River basin rainfall-runoff models for normal and extreme weather events

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ABSTRACT

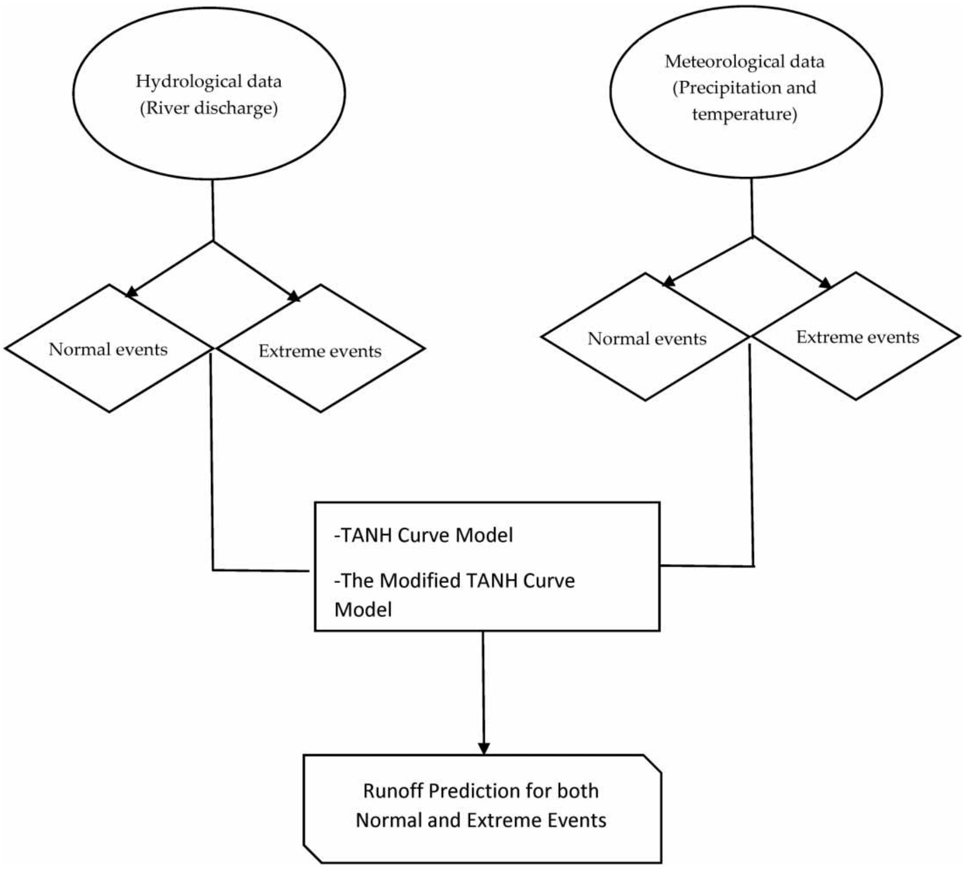
A variety of methods, including both modeling and non-modeling water balance techniques, are used in this study to estimate water availability allocated for different demands. The area under investigation is the shared Diyala River basin between Iraq and Iran, which is vulnerable to climate change impact and upstream control and aims to enhance watershed management. Two rainfall-runoff models were applied, the Tanh curve model and the modified Tanh curve model for runoff simulation at the Derbendkhan and Hemmrin hydrometric stations. Data from two meteorological stations in Iraq (Khanakin and Sulymania) and one in Iran (Sanandaj) for 20 hydrological years (2000–2020) was used. Some goodness of fit indicators were used to evaluate the reliability of the model outcomes, including the correlation coefficient, the root mean squared error, the mean absolute error, the deviation of runoff volume, and the index of agreement. Statistical analysis shows no statistically significant difference between observed and predicted runoff at all stations in winter, spring, and annual time scales when using the Tanh curve model, or for monthly and extreme wet events when using the modified Tanh curve method. The modified Tanh curve model was more accurate than the Tanh model and applied only to Sulymania and Sanandaj stations, as it required a considerable amount of precipitation in at least semi-humid areas.

Key words: Diyala River, extreme events, rainfall-runoff models, Tanh curve model, water balance models

HIGHLIGHTS

- Two empirical models are used to predict Diyala River runoff. The Tanh curve model produces a reasonable fit for winter, spring, and annual time scales, and the modified Tanh curve model gives a reasonable fit on a monthly time scale.
- The modified Tanh curve model performed better than the Tanh curve model.
- The modified Tanh curve model does not work for arid or semi-arid climates.
- Wet extreme events are represented well by the modified Tanh curve model, while the Tanh curve model could not represent dry or wet extreme events.

GRAPHICAL ABSTRACT



INTRODUCTION

The total water budget is a comprehensive evaluation of the water inflow to and outflow from the three interlinked systems (land, surface water, and groundwater) in a given water budget zone (Newsom *et al.* 2020). Precipitation, evaporation, transpiration, runoff, and water movement within the watershed, such as infiltration, recharge of groundwater, and reservoir storage, are all components in a water budget (Ontario Ministry of the Environment 2011; Rahi *et al.* 2019). It's a powerful tool for allocating river water for various demands. Uncertainty in accounting for water budget components, on the other hand, makes managing water resources challenging. There are basically two sources for this uncertainty: measurement errors and natural variability that occurs in components of the hydrologic cycle (Healy *et al.* 2007).

Both modeling and non-modeling techniques can be employed for generating a water budget. The most comprehensive method is the modeling technique, which involves utilizing numerical models to simulate processes in the land, surface water, and groundwater systems. Although it provides less precise results, the non-modeling approach employs assumptions, equations, and relevant available data to assist in comprehending the water budget (Al-Madhhachi *et al.* 2020; Lateef *et al.* 2020; Newsom *et al.* 2020). Various research utilizes different models to estimate water budget components and runoff. The WEAP-PGM model (Water Evaluation and Planning System – Plant Growth Model) was applied by Yaykiran *et al.* (2019) to the Sakarya River Basin in Turkey and gave an acceptable simulation of the stream flow. He *et al.* (2019) used the projections from 10 general circulation models to derive the Variable Infiltration Capacity (VIC) hydrological model for both mid-century and late-century to estimate changes in runoff in the major California watersheds. The results show that future runoff will be affected by climate change. Gao *et al.* (2018) used the SWAT (Soil and Water Assessment Tool) model to analyze the data. Findings produced by the HYPE (Hydrological Predictions for the Environment) model, used by Donnelly *et al.* 2016 to simulate runoff across Europe, reveal that it is efficient in simulating long-term means and seasonality, finding utility even for ungauged basins. Koneti *et al.* 2018 applied HEC-HMS (Hydrologic Engineering Center Hydrologic Modeling System) to analyze the impact of land use-land cover changes on the

Godavari basin. Their results indicate an expansion in built-up lands and cropland associated with deforestation that led to reduce the evapotranspiration and increase runoff.

Rainfall-runoff models could be designed to simulate extreme events such as the Australian water balance model (AWBM), which was developed for low flow cases using daily time steps and flood studies for hourly water yields (Boughton 2004). Extreme events have a detrimental impact on the water service system's environmental conditions, including water supply, and cause serious damage to the ecosystem and population. As a result of global warming, such events are anticipated to be even more frequent throughout the world, posing a greater threat to water resources (World Health Organization Regional Office for Europe *et al.* 2011 (WHO-Europe)). Severe meteorological and hydrological phenomena are either rare within a particular location's statistical records or accumulate from ordinary data that is not extreme separately (Murray & Ebi 2012). Many studies in recent years have shown an increase in extreme events and anticipate an increase in the future. Using observed data from stations in the area, trends in Middle East climate extreme indices revealed significant increasing trends in temperature-related indices with non-significant and spatially incoherent precipitation-related indices (AlSarmi & Washington (2014)). Al-Faraj *et al.* (2014) employed the Medbasin-monthly rainfall-runoff model to simulate runoff in the upper part of the Diyalal river basin under several drought scenarios, including reduced precipitation (between 0 and 40%) and increased potential evapotranspiration rate (between 0% and +30%). Their findings show that climate change has a significant impact on the basin's water resources, which demands immediate strategies and measures to overcome them. ESCWA United Nations Economic and Social Commission for Western Asia *et al.* (2017) used two representative concentration pathways (RCPs) of 4.5 and 8.5 to explore future extremes in the region during the mid- and late-21st century. They also employed three hydrological models (HYPE, VIC, and HEC-HMS) based on the output of two scenarios (RCPs) 4.5 and 8.5 to anticipate runoff in the Tigris and Euphrates basins in the mid- and late-century as well as simulate the impacts of extreme events. In the basin's headwaters, the findings point to minor increases in winter runoff and reductions in summer runoff. The results of general circulation models were investigated by Waheed *et al.* (2019) to explore the impact of future precipitation and temperature scenarios on the hydraulic structures in the Diyala River basin. Their findings suggest that the basin's hydrologic system will face major vulnerabilities during the next 25 years. The HEC-HMS model used by Hamdan *et al.* (2021) to imitate the Al-Adhaim river basin's runoff discharge peaks. Naqi *et al.* (2021) conducted statistical research for the Diyala River basin to determine trends in extreme temperature and precipitation indices, finding that temperature trends were more significant than precipitation trends, implying an increase in maximum temperature over minimum temperature.

The Diyala River basin has been chosen due to its vulnerability to the extreme events, as it has suffered from the consequences of flood and dry events. In addition, Diyala River is one of the most important rivers in Iraq as it is the major source of irrigation and municipal water for Diyala city. This study aims to assess the water budget and predict runoff of the Diyala River basin, based on data availability (from 2000 to 2020) with no real cooperation between the two transboundary countries in terms of how data is exchanged and water allocated for this shared basin. In this study, stream flow modelling was conducted on two stream gauges (Derbendikhan dam and Hemmrin dam) using data from three meteorological stations (Khanakin, Sanandaj, and Sulymania) to achieve the main goals of this study, which were to:

1. Apply the water budget equation in the Diyala River basin for both the upper and the middle parts using a non-modelling approach of two rainfall-runoff models (the Tanh curve and the modified Tanh curve) to predict the stream flow.
2. Analyze the impact of extreme weather events on the runoff.

This study provides reasonable, practical, and accepted methodology to assist water managers and decision-makers in developing better watershed management plans and strategies.

METHODS

Study area

The source of the Diyala River is in the Zagros Mountains, Sanandaj city, Iran. The Iraq-Iran border spans the river basin for around 30 km. The Tanjeru, Sirwan, and Wand rivers are the main tributaries, with many smaller tributaries shared by Iraq and Iran. The Tigris River joins the Diyala 15 km south of Baghdad. Its highest flow occurs in April, while its lowest flow occurs from July to November (ESCWA *et al.* 2017). The basin is located between 33 °2160 N and 35 °8330 N, and 44 °500 E and 46 °8330 E. It has a total length of 384 km and a drainage area of 33,240 km^2 (Figure 1).

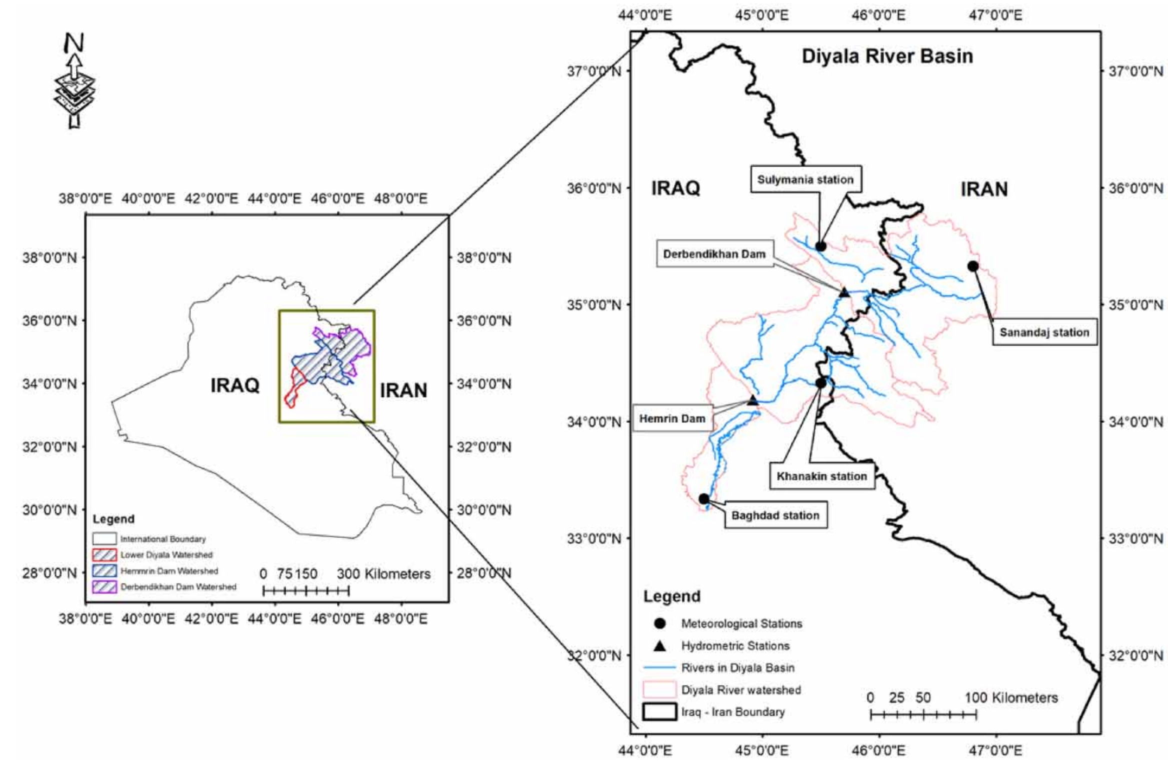


Figure 1 | Diyala river basin and the locations of the meteorological and hydrological stations.

The Diyala watershed's water management framework is separated into three areas. With an area of 17,900 km^2, the top section is mostly in Iran, and the rest is in Iraq, controlled by the Derbandikhan dam (Al-Faraj *et al*. 2014). With a transboundary area of 11,900 km^2, the middle part is located between the Derbandikhan and Hemrin dams. The lower part, which covers 2,800 km^2, is controlled by the Diyala weir. The Diyala Basin is divided into three climate zones, according to Al-Tamimi & Gamel (2016): it is semi-humid in the north, semi-dry in the middle, and dry in the south. The basin contains a dense network of dams and hydraulic works, with 12 dams in Iran's upper basin (five of them constructed between 1983 and 2010 and seven after 2010). The Diyala weir and two major dams (Derbandikhan and Hemrin) are located in Iraq's main river route. Within the Diyala Basin, irrigation projects consume the most water, followed by domestic use (Al-Faraj & Scholz 2015).

The average monthly discharge at Hemmrin dam inlet was 92.3 m^3/month, the minimum discharge was 2.4 m^3/month, and the maximum was 903.6 m^3/month during the study period (2000–2020). For Derbendikhan dam, the mean, minimum, and maximum monthly discharge were 90.9, 2.2, and 766.2 m^3/month, respectively.

Data

The Iraqi Meteorological and Seismology Organization provided monthly observed precipitation at Khanakin station between 2000 and 2020. The other two stations' data (Sulymania and Sanandaj) were obtained from the Global Historical Climatology Network database, (Table 1). (https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn), maintained on the National Oceanic and Atmospheric Administration server (https://www.ncdc.noaa.gov/cdo-web/). Actual evapotranspiration data with (4 km×4 km) resolution was retrieved from Terra climate data available at https://app.climateengine.com/climateEngine. Monthly discharge at two hydrometric stations: Derbendikhan dam's inflow (which regulates the upper Diyala river basin's outlet) and Hemmrin dam's inlet (which controls the middle part of the Diyala river basin) obtained from the Ministry of Water resources. Two water balance models were used to estimate discharge for both normal and extreme events, utilizing monthly data from the

Table 1 | Maximum, minimum, mean and standard deviation for precipitation (P) and temperature (T), Naqi *et al.* (2021)

				P (mm)			T(°c)		
Stations	**Country**	**Lat**	**Lon**	***Max***	***Min***	***Mean***	***Max***	***Min***	***Mean***
Khanakin	Iraq	34.18	45.26	512.3	142.7	281.2	25.54	23.18	24.02
Sulymania	Iraq	35.33	45.27	1,235.2	380.4	668.36	21.36	17.89	19.88
Sanandaj	Iran	35.33	47	752.8	169.72	344.79	15.67	12.82	14.5

20 hydrological years (which usually began in October and end in June) from 2000 to 2020. Sentinel-2 provides global land cover/land use for a yearly time series with 10×10 m of spatial resolution (Karra *et al.* 2021), as shown in Figure 2.

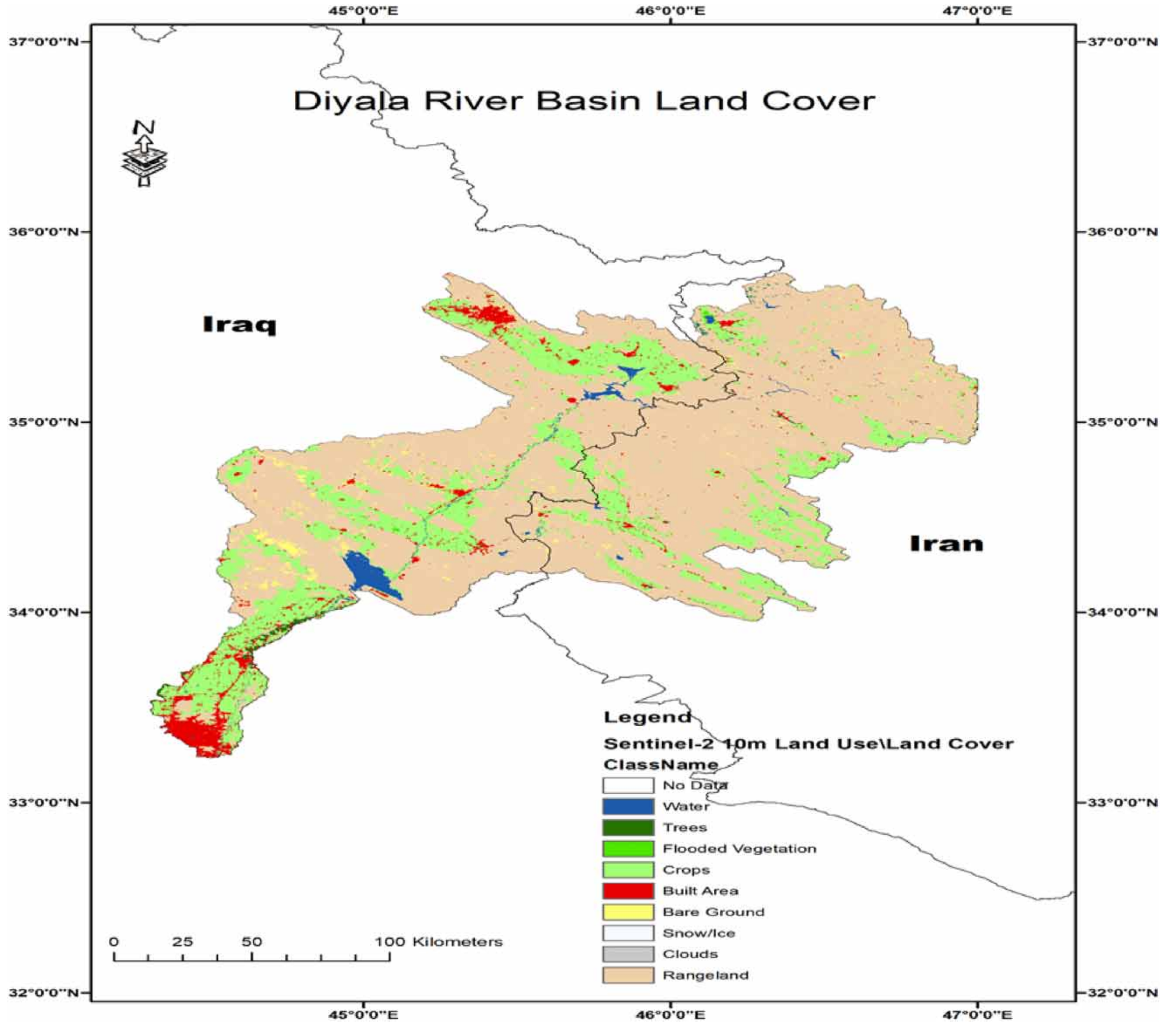


Figure 2 | Sentinel-2 land cover (10) m spatial resolution in 2019 for Diyala River basin.

Software

Many software programs were used to achieve the objectives of this study, as mentioned below:

1. The Agricultural and Meteorological Software to perform goodness of fit test.
2. Geographical information system for Diyala River basin delineated, area calculation, and land cover map.
3. Microsoft Excel for equations, figures, least fit square error, percentile.
4. Sigma plot for t-test and ANOVA test.

The Tanh curve model

A daily rainfall-runoff Tanh model was first developed by Boughton (1966) to predict the surface runoff from small ungauged ephemeral catchments (Equation (1)), using the following formula:

$$Qs = P - F \cdot \mathrm{Tanh}\ (P/F) \tag{1}$$

where $Qs =$ surface runoff, $p =$ the excess rain in (mm/day) after filling three storages (interception store by vegetation, upper soil unsaturated zone store, and excess infiltration temporarily held in top soil), $F =$ daily infiltration capacity (mm/day).

Grayson *et al.* (1996) modified the hyperbolic Tanh function to be applied to any data, including annual, seasonal, and monthly data (Equation (2)), to provide an effective site-based rainfall-runoff relationship, which is:

$$Q = (P - L) - F \times \mathrm{Tanh}(P - L)/F \tag{2}$$

where Q is surface runoff, P is rainfall, L is notional loss, and F is notional infiltration. All values are in mm to remove the effect of catchment area on stream flow. L and F are determined by plotting observed discharge against the associated rainfall to get the best fit curve. In this study, the least square fit was applied to choose the values for F and L.

The modified Tanh curve with cumulative surplus rainfall (CSR) model

Yihdego & Webb (2013) modified the Tanh water balance model and used it together with double mass curve analysis to distinguish the impact of land use change on stream flow from the climate variables (Equation (3)). This model is a useful tool for predicting runoff and estimating recharges for any given precipitation-evaporation system in a river basin, as follows:

- Taking monthly evapotranspiration and subtracting it from rainfall [$\in_{\mathrm{i}} = RF_i – ET_i$], and
- Accumulating the resulting departure values [$CSRi = \sum_{i=1}^{n} i$]

The values are added cumulatively to represent the physical process in the watershed, where stream flow is often delayed until the catchment has been adequately wet. Because the physical limit of depletion of the available water store is zero, all negative values are set to zero. Because rivers have flow even when there is no rain, they added an additional element G to the equation, which is the base flow owing to groundwater inflow. The modified Tanh equation then becomes:

$$Q = G + (CSR) - F \times \mathrm{Tanh}(CSR/F) \tag{3}$$

when the total cumulative simulated flow equaled the final cumulative real flow at each gauge, the best fit value of F (the notional infiltration) was discovered.

In the studied area, evapotranspiration far exceeds the rainfall during the spring, summer, and autumn months of the year, when cumulative surplus rainfall is always negative (set to zero), and streams are either dry or have only base flow or flow from the transboundary country of Iran. Starting in December, there might be a cumulative excess of rainfall over evaporation; *CSR* values rise to a maximum, and the extra rainfall becomes runoff. *CSR* values decline after April, when an excess of evaporation over rainfall occurs, until they reach negative (zero) once more.

Estimation of base flow

Base flow is a significant component of stream flow that is generated from groundwater and shallow subsurface storage and flows into the surface water (e.g., rivers, channels, streams, and lakes) over a certain period of time, as long as the water table remains above the surface water bottom (World Meteorological Organization [WMO] 2009). Assessing the base flow contribution to the stream flow is necessary to understand the hydrologic budgets of surface and ground water resources. During dry seasons, according to Smakhtin (2001), the base flow produces the whole runoff. According to Price (2011), basin variables such as aquifer characteristics, evapotranspiration, geomorphology, landscape changes, and soil types all influence base flow.

In this work, one of the most commonly used one-parameter digital filtering algorithms is applied, which is expressed in (Equation (4)) cited in Welderufael & Woyessa (2010).

$$q_t = \alpha q_t - 1 + 0.5(1+\alpha)(Q_t - Q_{t-1}) \tag{4}$$

where q_t is the filtered direct runoff at a time step t (m^3/s); q_{t-1} is the filtered direct runoff at a time step t–1 (m^3/s); α is the filter parameter; Q_t is the total runoff at time step t (m^3/s); and Q_{t-1} is the total runoff at time step t–1 (m^3/s). The base flow is:

$$G = Q_t - q_t \tag{5}$$

Al-Faraj & Scholz (2014) incorporate the flow duration curve method within digital filtering algorithms, as mentioned in Equation (4), to obtain the filter parameter with a high level of confidence by using daily flow data at the Derbandikhan hydrometric site for the upper part of the Diyala River basin and the Diyala Discharge Site for the combined upper and middle Diyala River basin. The results show that the filter parameter α with a value of 0.99732 produces a base flow index (BFI) that equates to the one derived from the flow duration curve analysis for both parts. This value of α is used in this study to extract the base flow for the upper and middle parts of the Diyala River basin using Equation (5).

Models' validation

The performance and the validation of the two rainfall–runoff models have been tested by comparing the predicted runoff, obtained by the models, with the observed runoff at the two dam's inlets (Hemmrin and Derbendikhan) using the goodness of fit indicators of the Agricultural and Meteorological Software available on: https://agrimetsoft.com/calculators/correlation%20coefficient. The results of the analysis should be considered valid, as data were filtered to eliminate odd values and obtain an accepted relationship between the predicted and observed runoff and to determine the range of rainfall and runoff amounts within which the model's results lie. In addition, the t-test (which was used to compare only two unrelated groups and indicate if there is a statistically difference between them at ($p < 0.05$)), and ANOVA test (which is used to compare the means of three or more unrelated groups to observe if any of them represent a statistically significantly difference) also have used to estimate the models credibility and show if there was a statistical difference between the observed and the predicted runoff or not.

RESULTS

The Tanh curve model

The Tanh rainfall-runoff model represented in (Equation (2)) is used at the monthly, seasonally, and annual time scales to predict runoff using observed precipitation data from three meteorological stations: Khanakin, Sanandaj, and Sulymania. Figure 3 shows results for Sulymania as an example at monthly and annual time scales, Figure 4 represents seasonal results. The discharge and precipitation data are filtered to remove the odd values and obtain more accurate results, see Table 2. At Sulymania station, some statistical indicators of the goodness of fit are represented to assess the model performance before and after filtering data, which are: the correlation coefficient (R), deviation of runoff volume (DV), index of agreement (IOA), mean absolute error (MAE), and root mean square error (RMSE). Generally, the model findings are much more accurate after filtering data and give reasonable results when compared with the observed data during annual, spring, and winter time scales for all indicators. During the monthly and autumn periods, only RMSE, MAE, and DV enhanced after filtering data, while IOA and R did not show any improvement.

The monthly data outcomes were the most inaccurate and cannot be accounted for due to their variability, followed by the modeled autumn results, which had the least amount of precipitation compared to the winter and spring seasons. The t-test for both of them indicated a statistically significant difference between observed and predicted data (P-value$<$0.001 and 0.012 for monthly and autumn data, respectively). The difference in the mean values of the two groups is greater than would be expected by chance. Figure 3 shows that the Tanh curve model can be run for Sulymania station (as an example) with monthly precipitation of less than 170 mm/month and monthly runoff of less than 50 mm/month. It also works for annual rainfall amounts between 350 and 950 mm/year and annual runoff of less than 300 mm/year.

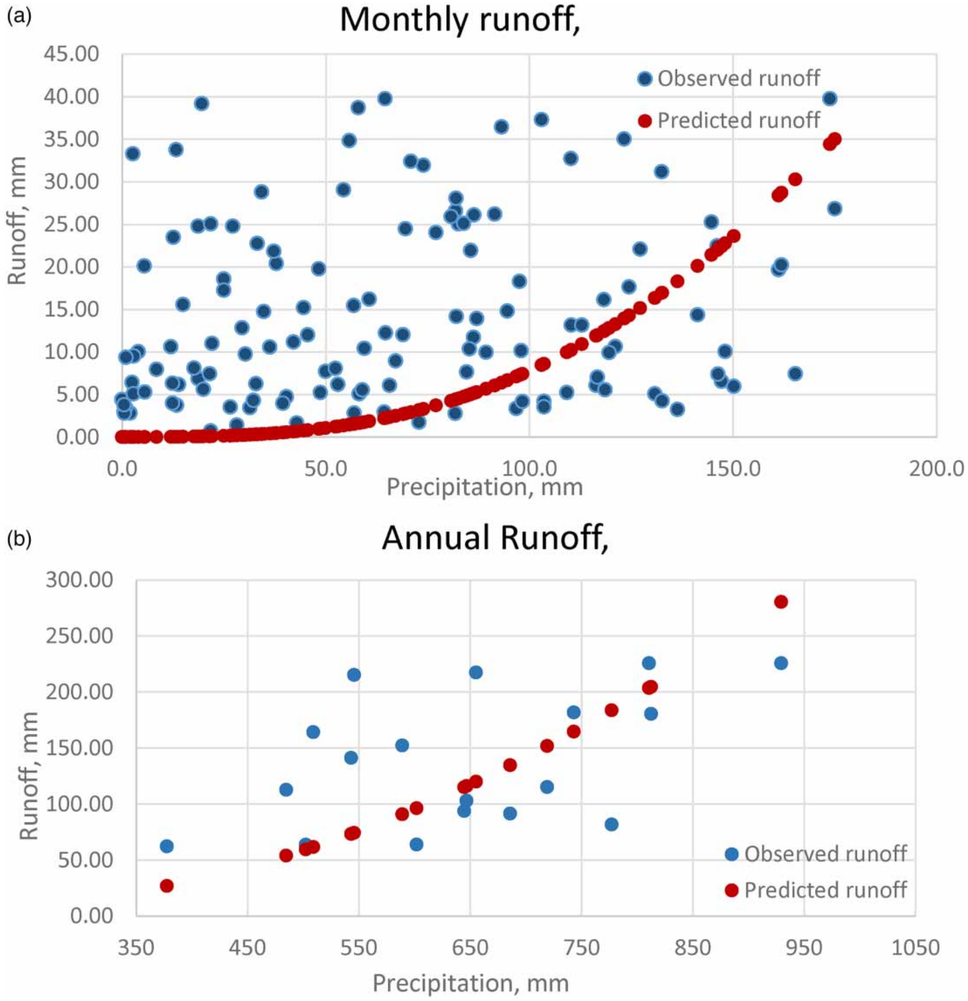


Figure 3 | Tanh curve model results for Sulymania city at (a) monthly, and (b) annual time scales.

At Khanakin and Sanandaj stations, the model can work for a monthly precipitation of less than 120 mm/month and a monthly discharge of less than 50 mm/month, and for annual precipitation amounts between 150 and 500 mm/year.

On the other hand, winter, spring, and annual data had accurate results. According to the t-test, there is not a statistically significant difference between observed and predicted runoff values for all of them (with *p*-values of 0.194, 0.588, and 0.458 for winter, spring, and annual data, respectively). The difference in the mean values of the two groups is not great enough to reject the possibility that the difference is due to random sampling variability. This indicates that the more rainfall amounts the better models' performance. Sulymania station gave reasonable results, as it had a considerable amount of participation that contributed to the total runoff of the upper part of the Diyala River basin. In addition, it is near to the Derbendikhan hydrometric station, which is used to obtain discharge data for the upper part of the basin, as both of them are located within Sulymania city. Figure 4(a) is for winter (December, January, and February) results, which reveal that the Tanh curve model can run well for amount of rainfall less than 500 mm/season and runoff of less than 90 mm/season. The model fit well precipitation amounts less than 200 mm/season, and runoff less than (140, and 90) mm/season for Khanakin and Sanandaj respectively.

Results for Sanandaj and Khanakin were similar to those of Sulymania. There was a statistically significant difference between observed and predicted data for the monthly and autumn time scales, with the difference in the mean values of the two groups are greater than would be expected by chance. On the other hand, based on the t-test, the findings for winter, spring, and the annual period were accepted without a statistically significant difference between the observed and predicted runoff. This finding reveals that the Tanh curve model's performance depends mainly on rainfall amount not on the location of the meteorological station

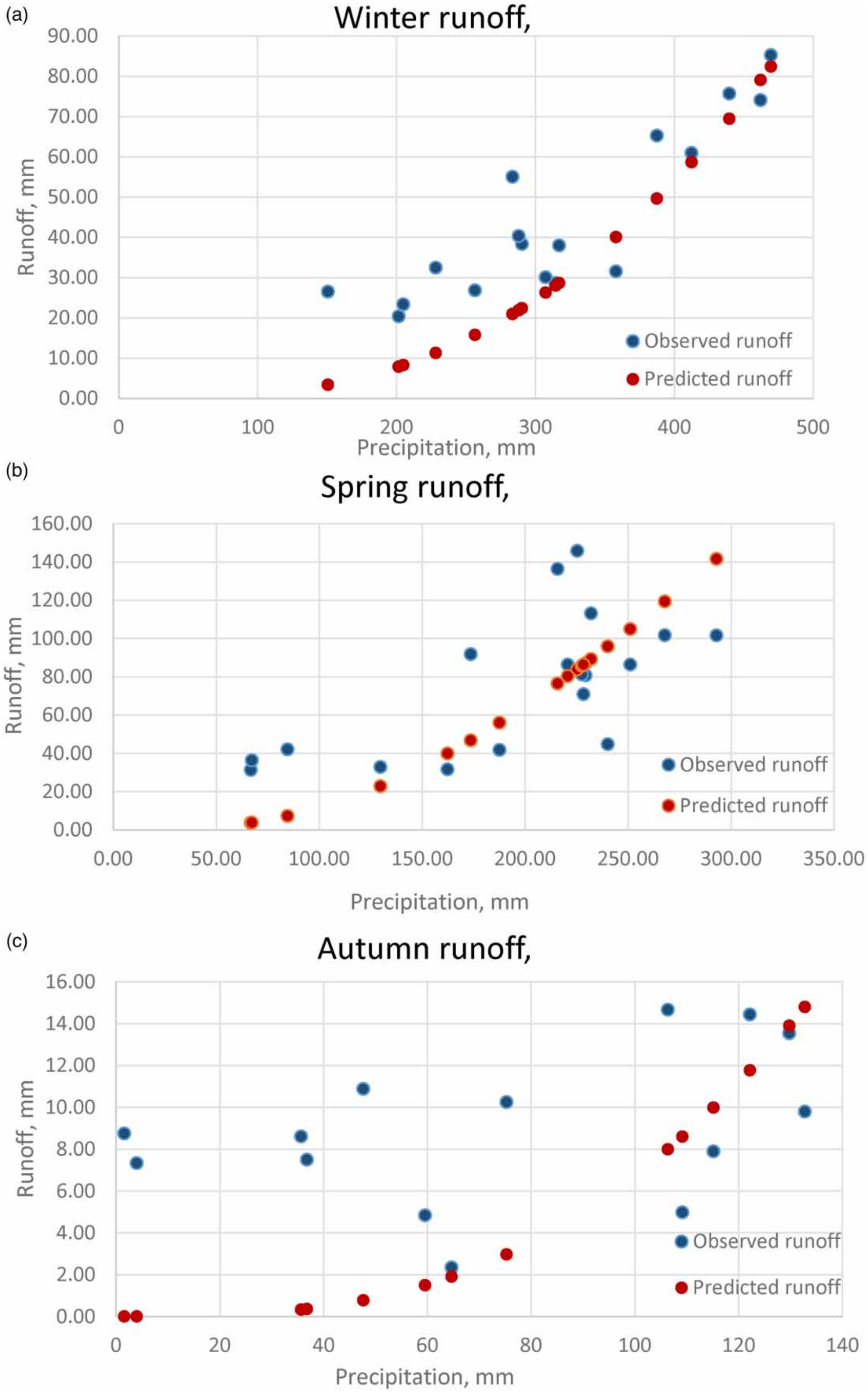


Figure 4 | Tanh curve model results at seasonal time scales for Sulymania city (a) winter, (b) spring, and (c) autumn.

within the basin and how far it from the hydrological station. As both Sulymania and Sanadaj are within the Derbendikan dam's basin, with Sanadaj much farther away from the dam than Sulymania, as shown in Figure 1. However, both models demonstrated the same performance during the rainy periods. Table 3 shows the t-test results for all stations.

Table 2 | The goodness of fit indicators to assess the Tanh curve model performance before and after filtering data at Sulymania station

	IOA	R	MAE	RMSE	DV%
Monthly					
All data	0.17	0.17	16.66	24.17	80.7
Filtered data	0.18	0.14	11.71	14.98	60.7
Annual					
All data	0.12	0.073	82.29	120.58	32.8
Filtered data	0.65	0.48	51.97	63.53	11.2
Autumn					
All data	0.39	0.34	37.3	46.19	56.8
Filtered data	0.34	0.33	5.64	6.68	46.2
Winter					
All data	0.38	0.34	37.31	46.19	56.8
Filtered data	0.89	0.91	12.1	14.83	23.7
Spring					
All data	0.66	0.5	35.39	47.38	8.5
Filtered data	0.78	0.65	26.54	32.16	9.3

Table 3 | T-test results between the observed and predicted runoff at the three stations using the Tanh curve model

	Monthly	Annual	Autumn	Winter	Spring
Sulymania					
Observed mean	14.26	138.37	9.22	44.25	75.43
Predicted mean	5.6	122.81	4.96	33.74	68.36
P- Value	0.0004	**0.23**	0.0059	**0.097**	**0.29**
Sanandaj					
Observed mean	14.52	145.57	10.31	50.62	66.22
Predicted mean	5.37	110.87	4.59	47.4	56.44
P- Value	0.000007	**0.12**	0.0013	**0.37**	**0.468**
Khanakin					
Observed mean	17.45	175.46	29.17	71.98	62.62
Predicted mean	5.63	175.46	13.19	65.39	59.82
P- Value	0.000006	**0.5**	0.004	**0.32**	**0.43**

Bold values represent **non-significant** statistical differences.

Extreme values were based on the 90th percentile of the monthly precipitation and monthly runoff to represent the wet extreme events, and the 25th percentile to simulate extreme dry events. Results for all stations showed a statistically significant difference between the observed and predicted data. This difference could be due to many reasons including: the variability of such events that makes their prediction very challenging, the insufficient observations, the role of atmospheric processes interactions at various scales (global, regional, and local) for the formation of extremes. Table 4 shows t-test results of extreme events that were applied using Tanh curve model. Figure 5 represented extreme wet events at Sulymania station as an example, and Figure 6 represent the extreme dry events at the same station.

Both *F* and *L* variables were estimated based on the least-square method using the solver add-in application in Microsoft Excel to get the best fit values for the simulated runoff. It's important to mention that *L* values for all

Table 4 | T-test results between the observed and predicted runoff for extreme values at the three stations using the Tanh curve model

	Precipitation 25th percentile Dry extreme	**Precipitation 90th percentile Wet extreme**
Sulymania		
Observed mean	7.72	41.2
Predicted mean	3.08	22.4
P- Value	0.000002	0.013
Sanandaj		
Observed mean	7.72	41.2
Predicted mean	5.28	5.31
P- Value	0.01	0.000002
Khanakin		
Observed mean	7.73	53.51
Predicted mean	4.76	34.26
P- Value	0.0034	0.015

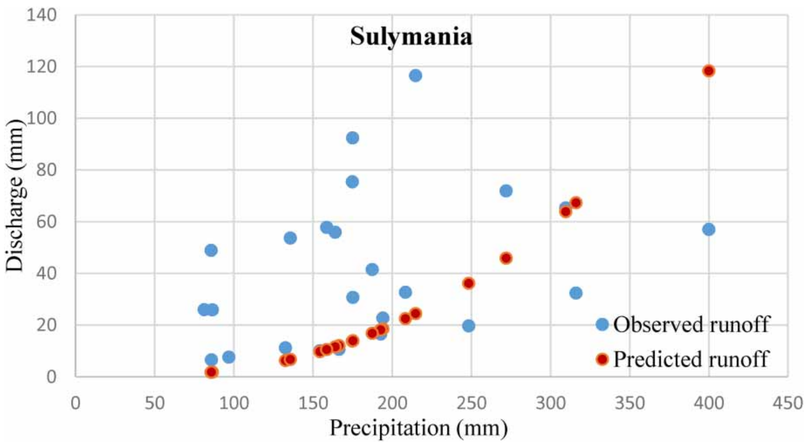


Figure 5 | The Tanh curve model results for extreme wet conditions for Sulymania station.

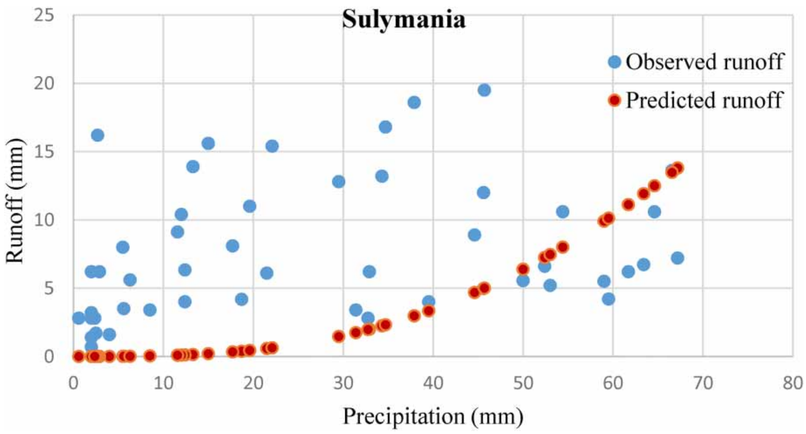


Figure 6 | The Tanh curve model results for extreme dry conditions for Sulymania station.

stations and all tested time scales were zero (except for annual data of Khanakin $L = 97$ mm/year). One reason for this is to compensate for the uncalculated discharge that comes from Iran by reducing the loss factor in this equation to increase the total predicted runoff. On the other hand, the F values, which represent water filtered into the ground, were changing from one station to another and from time to time, because infiltration rates depend on many different factors including: soil texture, soil-moisture content, land cover, soil temperature, etc.

Infiltration values at Khanakin station were the least among the three stations because it had the lowest amount of precipitation, while Sulymania with the highest amount of precipitation had the highest values of infiltration rate. For the same reason the wet extreme events had higher infiltration rates than the dry extreme events, as shown in Table 5. The goodness of fit indicators at the three stations using the Tanh curve model are shown in Table 6.

Table 5 | The values of *F* (notional infiltration) at the three stations using the Tanh curve model

	Monthly	Annual	Autumn	Winter	Spring
Sulymania					
F – Value	197.08	781.73	213.87	575.46	159.23
Sanandaj					
F – Value	73.87	231.32	263.35	76.14	62.27
Khanakin					
F – Value	57.74	1	166.69	55.81	10.76

Table 6 | The goodness of fit indicators at the three stations using the Tanh curve model

	IOA	R	MAE	RMSE	DV%
Monthly					
Sulymania	0.18	0.14	11.71	14.98	60.7
Sanandaj	0.1	0.08	12.45	15.84	63
Khanakin	0.22	0.2	14.63	18.14	67.7
Annual					
Sulymania	0.65	0.48	51.97	63.53	11.2
Sanandaj	0.21	0.17	64.92	83.67	35
Khanakin	0.81	0.69	65.72	76.33	0
Autumn					
Sulymania	0.34	0.33	5.64	6.68	46.2
Sanandaj	0.55	0.55	6.93	7.77	55.4
Khanakin	0.54	0.62	19.5	22.02	54.8
Winter					
Sulymania	0.89	0.91	12.1	14.83	23.7
Sanandaj	0.83	0.71	18.14	21.61	6.4
Khanakin	0.79	0.73	30.84	35.27	9.2
Spring					
Sulymania	0.78	0.65	26.54	32.16	9.3
Sanandaj	0.78	0.72	24.31	31.62	14.8
Khanakin	0.55	0.39	27.28	33.64	0.45

The modified tanh curve with cumulative surplus rainfall (CSR) model

Based on Equation (3), a simplified water budget model was applied to predict runoff using precipitation (*P*), actual evapotranspiration (AET), and base flow (*G*) data, as shown in Figure 7. Precipitation data was observed at meteorological stations. AET data has been obtained from Terra climate satellite data.

The base flow was calculated using two methods. The first is by using (Equations (6) and (7). The second, is by estimating its value using the least-square method to obtain the best fit value for the predicted runoff. The results of both methods were compared to the observed data using some statistical indicators to select the more accurate

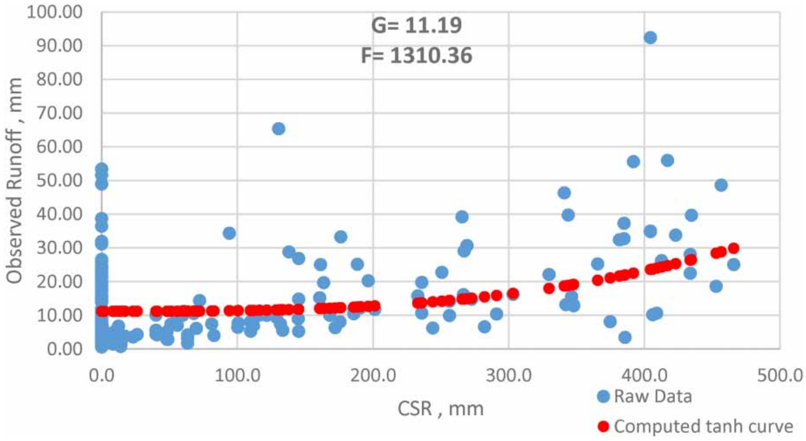


Figure 7 | The modified Tanh curve model results at monthly time scale for Sulymania city.

one. Modelled runoff with the constant G (which obtained by the best fit value using solver application) was more precise than with G values obtained from the filtered direct runoff equation for all indicators (except for R, where there was not any difference) for both normal and extreme data. This is consistent with Yihdego & Webb (2013) work, in which they estimate one constant value for G for each station using the least-squared method to compensate it in the modified Tanh model.

The monthly runoff values based on t-test did not show a statistically significant difference between observed and predicted data that were obtained from using the modified Tanh curve equation with p values equal to 1 (i.e. $p > 0.05$). The goodness of fit indicators revealed strong relationship between the observed and the predicted monthly runoff.

Table 7 shows goodness of fit statistics at Sulymania and Sanandaj stations, indicating that the modified Tanh curve model works better for Sulymania station than Sanandaj station. One important reason for this is that Sulymania had a higher amount of precipitation than Sanandaj, indicating that higher amounts of precipitation at a station leads to more accurate predicted runoff.

Table 7 | The goodness of fit indicators at Sulymania station using the modified Tanh curve model

	IOA	R	MAE	RMSE	DV%
Monthly CSR					
Sulymania	0.73	0.64	8.73	12.21	0
Sanandaj	0.46	0.42	10.28	14.34	0
Extreme CSR					
Sulymania	0.73	0.63	11.77	15	0
Sanandaj	0.56	0.49	13.28	16.81	0

The one-way ANOVA test for analysis of variance between observed and predicted monthly data showed that the Tanh curve model did have a statistically significant difference with the observed ($p < 0.001$). The mean was 14.054 for the observed runoff and 5.6, and 5.37 for the predicted runoff at Sulymania and Sanandaj stations, respectively. However, the ANOVA test for analysis of variance between observed and predicted monthly runoff showed that the modified Tanh curve model did not have a statistically significant difference ($p = 1$; mean of 14.054) for all the observed and the predicted runoff. This demonstrates that the modified Tanh model performed better than the original Tanh model, given that this model includes more of the water balance parameters than the Tanh curve model.

Extreme values were applied for only wet conditions based on the 90th percentile of precipitation with the 10th percentile of AET when using the modified Tanh curve model because this model cannot work for dry conditions, where P-ET is a negative value they set to zero to simulate the physical conditions. According to the t-test, the findings show no difference in the mean values of the observed and predicted data, which are 21.59 for all of them. There is not a statistically significant difference between the observed and modeled groups (with p-value equals 1). This confirm the conclusion that this model work well in wet conditions. Figure 8 shows extreme values at Sulymania station as an example.

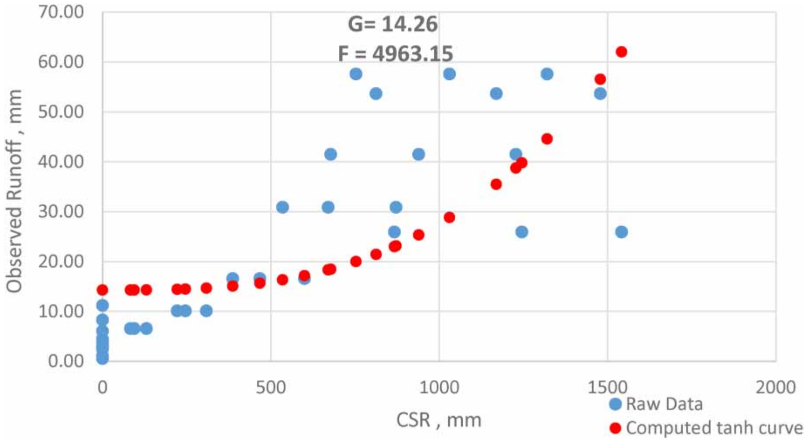


Figure 8 | The modified Tanh curve model results for extreme wet condition at Sulymania city.

It is worth mentioning that the modified Tanh curve model can be applied only to the Sulymania and Sanandaj stations that had higher amount of precipitation and lower amount of AET than Khanakin station. This implies that it is only applicable to at least semi-humid climate regions with a significant amount of precipitation.

DISCUSSION

In this study, two models were used to predict discharge at two hydrometric stations within the Diyala River basin using observed precipitation and temperature data over the years (2000–2020). The first one was rainfall-runoff Tanh curve model, which represent an empirical model as it use only precipitation data as an input. The second was the modified water balance Tanh curve model, that consider as conceptual model as it includes many of water balance components. The later results applied only on Sulymania and Sanandaj stations because it can be applied on area with relatively high amount of precipitation (classified within the Simi-humid climate). The conceptual model results were more accurate than the empirical model according to the ANOVA test. This corresponds with Sitterson *et al.* (2017), who note that the conceptual models are more complicated but more accurate than the empirical models.

In this study AET from satellite data has used instead of the reference evapotranspiration ($ET_{\circ}$) which had used in the origin paper by Yihdego & Webb (2013). AET seemed to have a better performance than the $ET_{\circ}$ when applying them to account for CSR in the modified Tanh curve model.

The Tanh curve model yielded better results at annual and seasonal time scales (except for autumn) than at the monthly scale, which approved the recommendation of Grayson *et al.* (1996). It would be best to use annual data or at least seasonal data to drive the values of the notional loss (L) and the notional infiltration (F), as both could satisfy the models' need for approximately constant values of L and F, while monthly data could not meet this demand.

The impact of extreme events on runoff is also examined in this study. The wet extreme events determined by the percentile-based indices, precipitation and discharge with the 90th percentile corresponding to AET with a 10th percentile. On the other hand, the extreme dry events represented by precipitation and discharge with a 25th percentile correspond to AET with a 90th percentile. The wet events using a modified Tanh curve model gave considerable results, with non-significant differences between the observed and predicted runoff when using the t-test. Both wet and dry events had significant differences when using the Tanh curve model. ACSAD and ESCWA (2017), used the 90th percentile of the highest daily records for precipitation and temperature to represent wet and dry events, consequently, as well as variations in the frequency of extreme flows.

To obtain a comprehensive understanding on the impact of extreme events on the Diyala River runoff, a close examination on the monthly range of the rainfall and runoff amounts for normal, wet, and dry events within which the Tanh curve model run would be of great help. The normal events Figure 3(a) run within rainfall range (0–200) mm and runoff range (0–45) mm, the wet events (Figure 5) run within rainfall range (70–400) mm, and runoff range (5–120) mm, and the dry events (Figure 6) within rainfall range (0–70) mm, and runoff range (0–22) mm. The maximum edge of each range reveals that for wet events if the rainfall duplicate (from 200 to 400) mm, this would lead to an increase in runoff about three times more than the normal events runoff (from 45 to 120) mm. The maximum edge for dry events showed that if the rainfall decreases by about ⅓ (from 200 to 70) mm, this would cause runoff reduction by about ½ (from 45 to 22) mm. This underscores the fact that extreme weather and climate events have a great impact on water resources, thus compounding the impact of climate change itself. This finding is consistent with many other studies which explored the sensitivity of the Diyala River runoff to different dry and wet scenarios. For example, Al-Faraj *et al*. (2014) examined the impact of a severe drought scenario on the runoff in the upper part of the Diyala River basin. Their results showed that drought has a significant impact on the basin's water resources, which demands urgent measures to overcome it. Waheed *et al.* (2019) investigated the outcomes of precipitation and temperature from general circulation models to simulate the runoff in the Diyala River basin, revealing a significant risk in the Diyala River's hydrological system in the near future.

Our findings help in predicting the runoff when using empirical and conceptual models in the area of data scarcity to assist decision-makers in making proactive plans for better managing the watershed. This study is consistent with many other studies that use empirical and conceptual models to predict discharge and give valid results to quantify hydro-climate variables on a river basin scale (Al-Faraj & Scholz 2014; Ajaaj 2018; Rahi *et al.* 2019).

CONCLUSIONS

Water budget calculations play a crucial role in water allocation across different sectors. They serve to facilitate water conservation, reducing water management costs, and managing the available water resources during drought seasons. Therefore, water balance studies are critical, particularly for water-stressed areas. It's a fact that there is a huge lack of hydrometeorological data in general and in shared basins in particular in our region, which makes water balance estimation using the modeling technique difficult with a wide range of uncertainties. This work aims to investigate non-modeling approaches to account for the water budget components using as little data as possible to provide a general understanding of the Diyala River basin. Our study makes an important contribution to climate and water research, especially for extreme-related events. It helps decision-makers to improve management plans for the studied basin through a better understanding of the water balance across the basin based on real data and linking it to the incoming discharge at two dams in Iraq.

The authors used observed precipitation data from three meteorological stations and observed discharge data from two hydrometric stations across the Diyala River basin from 2000 to 2020 to examine the performance of empirical rainfall-runoff and conceptual water balance models at monthly, seasonal, and annual scales, utilizing the Tanh curve model and the modified Tanh curve model. Both extreme and normal events were tested during this study to analyze the predicted runoff versus the observed data. Both models work well for Sulymania and Sanandaj stations, with the performance of the modified Tanh model being more accurate according to the ANOVA test. However, the modified Tanh model did not work for Khanakin station (which has a semi-arid climate) as it required a considerable amount of precipitation. The Tanh curve model results yielded significant differences between the observed and predicted runoff during autumn and monthly time scales.

It should be noted that integrated water resources management demands data access, the validity of the information, and a better perception of present and future events. Moreover, the quantity of data in this study is a key constraint. More data over a longer time span and more stations within the Diyala watershed are required, primarily within Iran. Such data would lend the results of this study more credibility. The authors recommended using different empirical water balance models for both observed and simulated data in the future. This will enable us to obtain more precise results for both extreme and normal events in regions with data scarcity.

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AUTHOR CONTRIBUTIONS

The lead author, Noor M. Naqi, envisioned the research topic and collected and analyzed the data as part of her Ph.D. thesis. Abdul-Sahib T. Al-Madhhachi and Monim H. Al-Joboori supervised the research and supported the interpretation of the results and manuscript preparation.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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