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A comparative analysis of continuous and event-based hydrological modeling for streamflow hydrograph prediction

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A precise evaluation of streamflow hydrographs and their attributes is one of the key components of hydrological applications. This research investigates a comparative analysis between event-based and continuous hydrological modeling of streamflow using the HBV rainfall-runoff model. The Dez river basin in southwest Iran was selected as a case study. Model performance was examined for a total of nine streamflow events during time period 2012–2019. The results of the model were compared for event-based and continuous simulations of streamflow using goodness-of-fit measures involving Nash-Sutcliff efficiency (NSE), normalized root mean square error (NRMSE), and mean absolute percentage error (MAPE). Besides, the most sensitive parameters were identified using sensitivity analysis. Results revealed that although HBV model has a reliable performance for both modeling approaches, continuous modeling of streamflow hydrographs slightly outperforms the EB simulation approach. These outcomes provide an efficient information to improve the operation of water systems and hydrological forecasts.

KEY WORDS: Streamflow hydrograph, HBV rainfall-runoff model, event-based simulation, continuous modeling

Introduction

Streamflow forecasting, as one of the main components of hydrological science, has great importance in water resources management in terms of optimal operation of reservoirs, water supply, flood risk management, and water structure design (Meshram et al., 2022). Rainfall-runoff (RR) models are commonly used to simulate streamflow (Wijayarathne and Coulibaly, 2020; Kumari et al., 2021). The process of converting rainfall to runoff is variable in different RR models. As described by Salvadore et al. (2015), RR models can be categorized based on their spatial variations (lumped, semi-distributed, and distributed), temporal changes (continuous and event-based modeling), and process definition (physical models or data-driven models). Similar classifications can be found in Okiria et al. (2022), Cunderlik (2003), and Lees et al. (2021). Therefore, RR models are selected based on the physical characteristics of basins and accessibility to data.

According to temporal category, event-based (EB) and continuous (CS) simulation approaches are the most well-known subcategories. EB modeling simulates the rainfall-runoff process in a catchment for an individual rainfall or streamflow event that may last several hours up to several days. In contrast, CS modeling simulates the rainfall-runoff process over a long period of time, from a few months to several years (Hossain et al., 2019).

Some scholars assessed the performance of different hydrological models to simulate EB and CS rainfall-runoff processes. In this regard, Hossain et al. (2019) carried out a comparative analysis using the storm water management model developed by the Environmental Protection Agency, USA (EPA-SWMM) in producing total runoff hydrographs and direct runoff hydrographs. They showed that EB modeling of runoff has more precision than CS modeling. A number of researchers have observed that an EB approach performs better than a CS approach for simulating runoff (Chu et al., 2009; De Silva et al., 2014; Azmat et al., 2017). In addition, Katwal et al. (2021) illustrated the reliability of the HEC-HMS model to forecast streamflow for both modeling approaches in the Zijinguan catchment in China. Cunderlik and Simonovic (2005) obtained a better fit using CS modeling of hydrological extremes in a southwestern Ontario river basin under future climate conditions.

Nowadays, various hydrological models, e.g., EPA-SWMM, soil and water assessment tool (SWAT), Hydrologic Engineering Center's Hydrological Modelling System (HEC-HMS), modular modeling system (MMS), and Hydrologiska Byrans Vattenbalansavdelning (HBV), have been developed to

estimate runoff worldwide (Hossain et al., 2019; Jaberzadeh et al., 2022). While each model has its own advantages and disadvantages, the HBV model is able to simulate RR modeling as CS and EB. This model has been used for water balance (Erlandsen et al., 2021), climate change (Djebbi and Dakhlaoui, 2023; Sabova and Kohnova, 2023), and related simulations concerning groundwater (Wang et al., 2021).
Previous studies revealed that the HBV model was successfully applied in different basins throughout the world due to its robustness, simplicity, and reliability. Moreover, it does not require a large number of input data (Krysanova et al., 1999). For instance, Tibangayuka et al. (2022) shown the proficiency of the HBV model in comparison with the data-driven model for simulating streamflow in a data-scarce high-humidity tropical catchment in Tanzania. In another study by Grillakis et al. (2010), the HBV model's performance was evaluated to predict flash floods in Slovenia. The results of their research represent the high efficiency of this model by producing values of the Nash-Sutcliffe coefficient in the range of 0.82-0.96. Besides, Kuban et al. (2021) analyzed the potential of the HBV model to simulate runoff using the satellite remote sensing of soil moisture (ASCAT) dataset over 209 catchments located in different climate zones of Austria. Based on the results of their research, a robust simulation of runoff was demonstrated in more than 27 percent of the studied catchments. Tanhapour et al. (2023) investigated the HBV model performance to forecast ensemble reservoir inflow under two scenarios, including ensemble forecasts (simulation using post-processed ensemble precipitation forecasts as input to the model) and deterministic forecasts (simulation using observed precipitation data). They indicated that ensemble forecasts are more reliable than deterministic forecasts to simulate reservoir inflow hydrographs. Therefore, previous studies have shown the successful application of the HBV model for forecasting streamflow.
To our knowledge, in none of the reviewed studies, the HBV hydrological model has been evaluated for CS and EB simulation of streamflow hydrographs. Therefore, the current research explores the accuracy of estimating streamflow using the HBV model based on CS and EB rainfall-runoff modeling approaches.

Material and methods

Case study

The Dez river basin, located upstream of the Dez reservoir, was selected as a case study. It is formed by the connection of the Bakhtiari and Sezar rivers in the south-western of Iran. This river is 120 km long and joins the Karun River in the area of Band-Ghir, downstream of the Dez reservoir. Fig. 1 demonstrates the location of the Dez basin, synoptic rainfall station, and hydrometric station.
The Dez basin has been located in the semi-arid mountainous region, in the range of latitudes from 32°, 35' to 34°, 07' North, and longitudes from 48°, 20' to 50°, 20' East. The basin shares its boundary with the Karkheh basin in the west, the Ghareh Chay basin in the north, and the Karun basin in the east and south (Tanhapour et al., 2023). The basin covers an area of 16213 km^2. The discharge data for the Taleh-Zang hydrometric station, upstream of the reservoir, was used to simulate streamflow hydrographs. The average annual discharge of Taleh-Zang hydrometric station is 193 m^3 s^{-1} during 2012–2019. Table 1 indicates the average annual precipitation and temperature of the synoptic stations during selected time period.

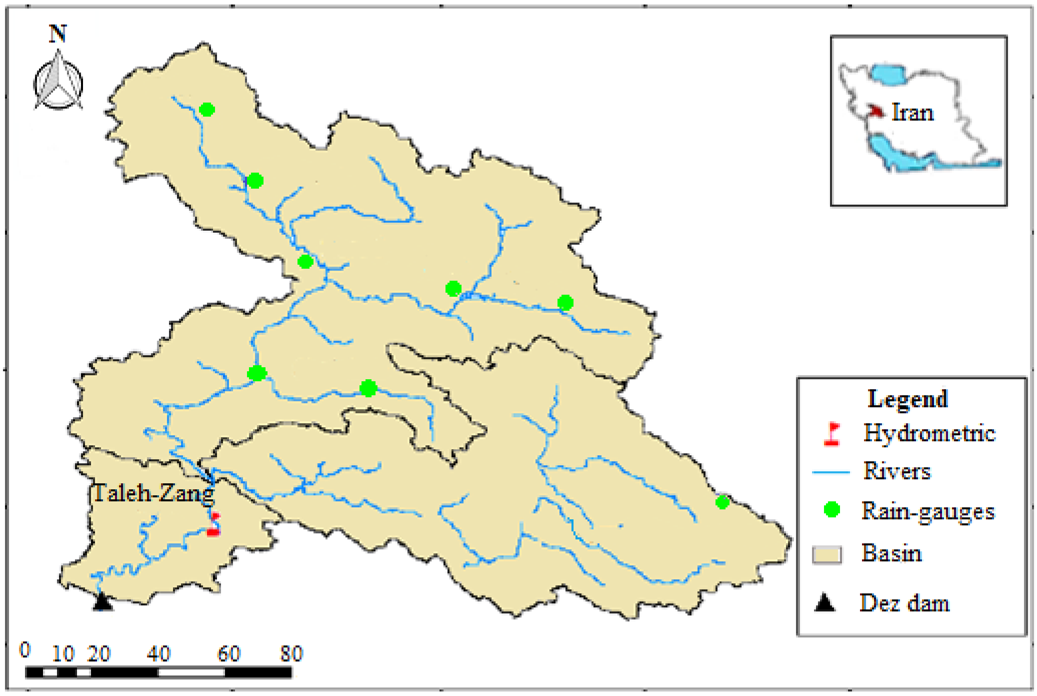

Fig. 1. The location of Dez river basin, hydrometric station, and rain gauges.

A set of variables, including precipitation, temperature, potential evapotranspiration, and discharge, were employed as inputs to the HBV hydrological model. Precipitation was interpolated uniformly all over the basin using the inverse distance weighting (IDW) method (Jeong et al., 2020). The temperature was estimated by interpolation between the temperature and elevation of synoptic stations. Besides, potential evapotranspiration was obtained using the empirical equation presented by Lawry-Johnson (Lowry and Johnson, 1942).

The input data were available at daily time steps during 2012–2019. The HBV model was calibrated during 2012–2015 and validated during 2016–2019. The model's efficiency was compared for two modeling approaches (CS and EB rainfall-runoff modeling) over the selected streamflow events, which were shown in Fig. 2. This figure indicates streamflow and precipitation time series in the calibration and validation stages. The streamflow events were chosen during peak flows. Table 2 displays the values of peak discharge for the streamflow events.

Table 1. Average annual precipitation and temperature of the synoptic stations

Station	Annual Precipitation [mm]	Annual Temperature [°C]
Aligudarz	727	13.41
Azna	496	13.12
Borujerd	541	15.94
Dorud	641	16.66
Shulabad	1048	15.3
Sepiddasht	679	20.64
Silakhor	491	15.1
Fereidunshahr	692	11.88

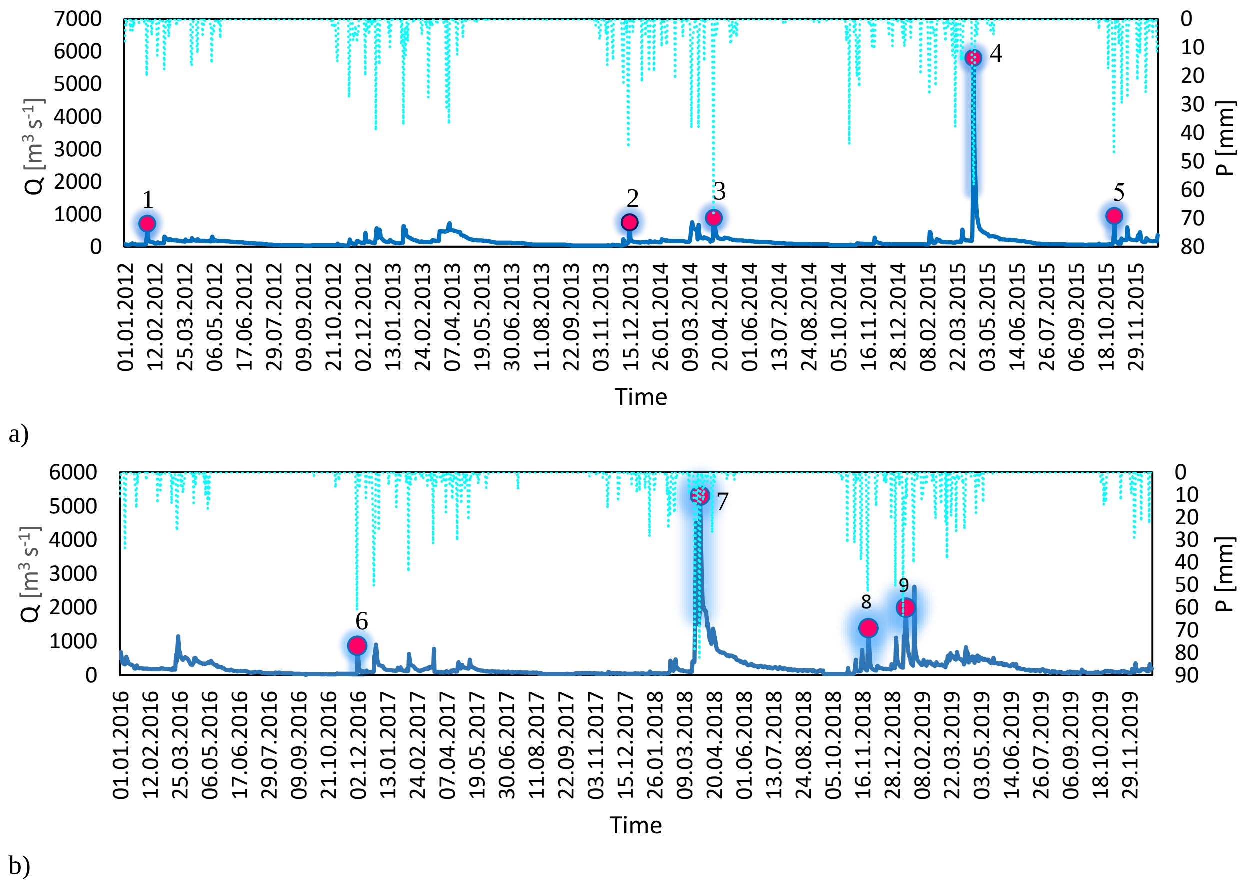

Fig. 2. Observed precipitation and streamflow time series in a) calibration period (2012–2015); b) validation period (2016–2019).

Rainfall-runoff model

The Hron hydrological model, as a modified version of the HBV model, was applied for simulating streamflow (Valent et al., 2012). This model includes three sub-models, e.g., snow accumulation and melt, soil moisture, and runoff response. Fig. 3 demonstrates the model's structure.

The model estimates runoff based on the parameters used in the snowmelt and soil moisture sub-models (see legend of Fig. 3). The runoff response sub-model transforms the estimated runoff into the discharge at the watershed outlet. In the runoff response, there are two storage zones, the upper storage zone and the lower storage zone. They are linked using constant percolation (perc). Runoff in the upper zone (Q_0) is swiftly triggered when the water level exceeds a threshold limit (L), while the other outlets are slow to respond. In the upper and lower zones, K_0, K_1, and K_2 represent recession coefficients that control runoff (Parra et al., 2018). Finally, it applies the triangular weight function (MAXBAS) for routing the produced runoff.

Calibration and validation of the model

The values of parameters were estimated automatically using genetic algorithms (GA). The Nash-Sutcliff efficiency (NSE) coefficient was used as an objective function to find the optimal values of the parameters based on the following equation (Nash and Sutcliffe, 1970):

Table 2. Selected streamflow events

Event No	Base-time	Time Period [day]	Peak flow [m^3 s^{-1}]
1	30 January–08 February, 2012	10	708
2	11 December–20 December, 2013	10	742
3	09 April–20 April, 2014	12	882
4	11 April–25 April, 2015	15	5799
5	26 October–04 November, 2015	10	938
6	28 November–07 December, 2016	10	858
7	30 March–06 April, 2018	8	5298
8	23 November –30 November, 2018	8	1381
9	12 January–27 January, 2019	16	1986

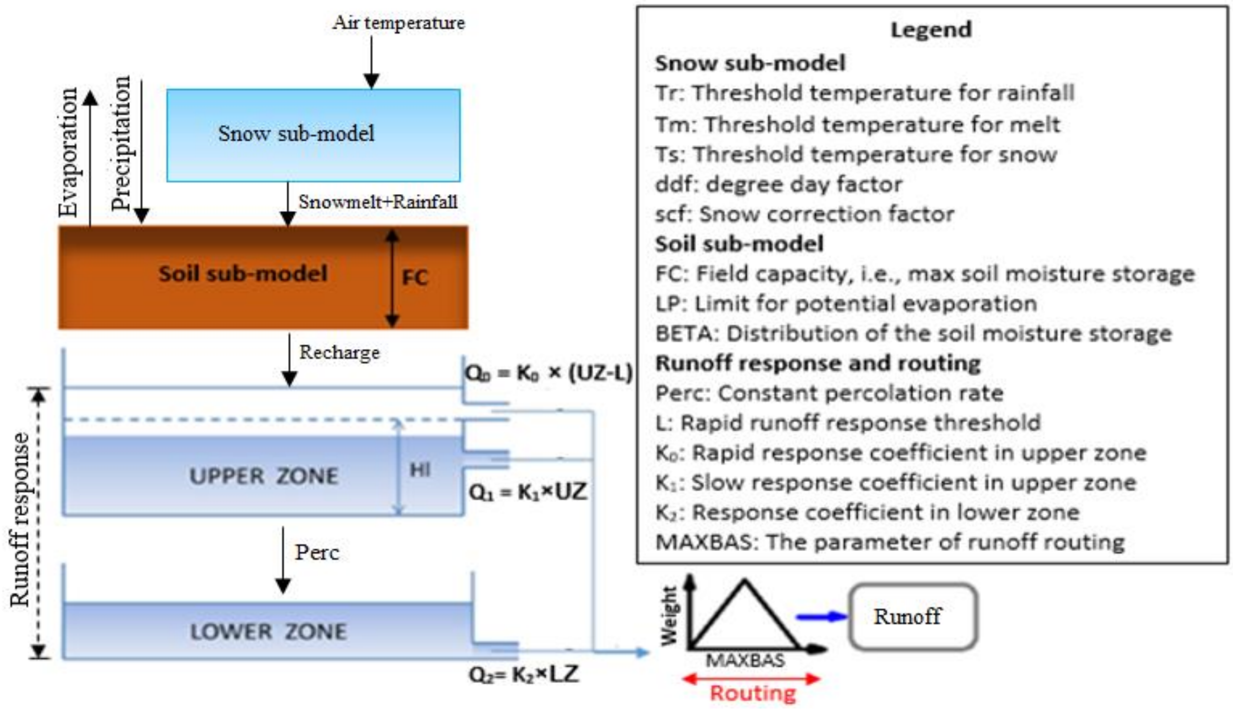

Fig. 3. The HBV model structure and parameters used in this study (Tanhapour et al., 2023).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{sim} - Q_{obs})^2}{\sum_{i=1}^{N}(Q_{obs} - \bar{Q}_{obs})^2} \quad (1)$$

where
Q_{obs} and Q_{sim} – are observed and simulated flow [$m^3 s^{-1}$], respectively,
$\bar{Q}_{obs}$ – is the mean observed flow,
N – is the total number of records.

The model has been continuously calibrated for one month before the time period of streamflow events. For event-based calibration of the model, it was calibrated only during the base-time of selected events, which were shown in Table 2. The optimal values of the parameters were obtained using the calibration of the model for each modeling approach (Katwal et al., 2021). Moreover, to identify the most sensitive parameters, the values of the parameters were increased and decreased as much as 20% of their initial values. Then, it was investigated the maximum percentage of variations created in the model output using the variation of parameters (Tanhapour et al., 2022).
Continuous validation of the model has been carried out since two months before the time period of the selected events. In the next step, event-based validation of the model was performed during the streamflow events' base-time (Events 6–9). It is worthy to note that in both modeling methods, the optimal values of the parameters derived from calibration of similar streamflow events (with roughly the same peak flow) were used to investigate the validity of the model (Katwal et al., 2021).

Results and discussion

Continuous modeling of streamflow hydrograph

The results of the CS simulation of streamflow time series are depicted in Figs. 4 and 5 for the calibration and validation periods, respectively. Based on a visual comparison, it appears that the trend in the simulated time series is reasonably close to that of the observed series. However, it is obvious that there is a relative compatibility between simulated and observed peak flows. In addition, the results of sensitivity analysis of the parameters were presented in Table 3. The results indicated that the most sensitive parameters in reproducing streamflow are, respectively, L, maxbas, K1, scf, and BETA, considering the threshold limit for the NSE index of approximately 19–20% (Tanhapour et al., 2022). This means that by altering the values of the mentioned parameters, the NSE index was changed by a maximum of 20%. As a result, it can be inferred that these parameters greatly influence the model's precision compared to the others. Similar results were obtained by Brziak et al. (2021). They compared the lumped and semi-distributed versions of the HBV model in terms of the variations in the snowmelt sub-model parameters. This research was performed over 180 catchments in Austria. They divided the catchments into three groups based on their mean elevation. The results revealed the superiority of the semi-distributed versions of the HBV model compared to the lumped version.

Comparing continuous and event-based modeling of streamflow

Streamflow hydrographs were simulated as CS and EB using the HBV hydrological model. Fig. 6 shows the outcomes of the HBV model used for simulating streamflow during the calibration period. In this figure, the observed hydrograph along with CS and EB modeling of streamflow were displayed using blue, green, and red lines, respectively. As it can be seen, there is a little difference in the shape of stream hydrographs for both types of modeling approaches in the calibration period. However, in the majority of cases, the CS modeling approach has a better fit with observed streamflow in terms of peak flow, rising limb, and falling limb. In fact, it is possible for a model to take into account the antecedent status of a basin, e.g., antecedent rainfall, streamflow, and soil moisture, in CS modeling. For this reason, the model has higher efficiency for CS modeling compared to EB modeling. Moreover, CS modeling of streamflow considers both infiltration and evapotranspiration losses, whereas EB modeling only includes evapotranspiration losses.
The numerical results of the model's performance were presented in Table 4 for the calibration period. The average values of the NSE and NRMSE criteria, respectively, were estimated equal to 0.93 and 0.19 for the CS modeling approach. Similarly, they obtained 0.93 and 0.23 for the EB modeling approach, respectively. It represents the validity of the HBV model in reproducing streamflow hydrographs for both modeling approaches.
Fig. 7 indicates the graphical plot of streamflow hydrographs in the validation stage. It is clear that the model's error has been increased to estimate peak flow for both modeling approaches. Similar to the calibration stage, the simulated streamflow for CS modeling has a better match with the observed streamflow compared to the EB approach. It is worthy to note that hydrological processes and, subsequently, rainfall-runoff modeling are influenced by catchment urbanization and land use changes. Therefore, the streamflow generation process is different for diverse catchments. Consequently, it can be inferred that there is a clear distinction in hydrographs generated using models depending on the catchment characteristics. Consequentially, the models' performance is variable for CS and EB modeling of streamflow from one catchment to another.
Table 5 illustrates the values of goodness-of-fit measures to simulate streamflow in the validation stage. The average values of the NSE index for CS and EB modeling of streamflow have obtained 0.83 and 0.8, respectively, representing more accurate results of CS rainfall-runoff modeling. Generally, it can be said that the HBV model has robust efficiency for both modeling approaches in producing streamflow hydrographs.

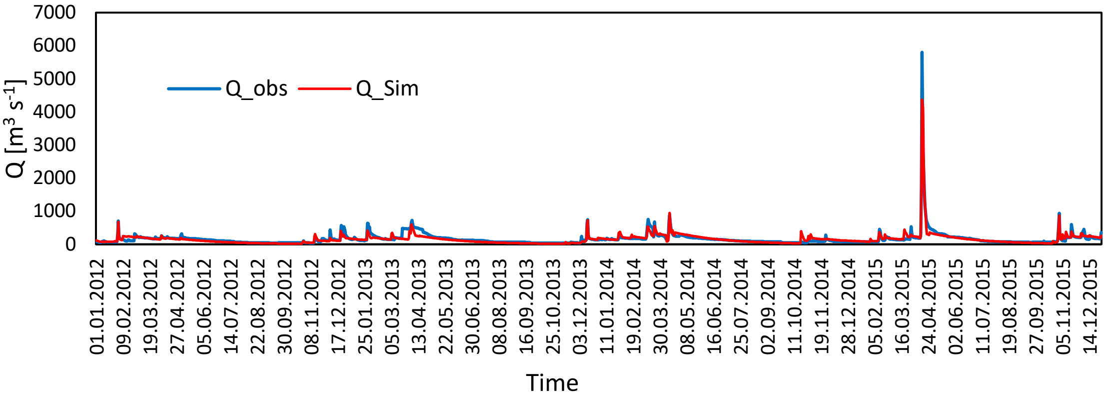

Fig. 4. Comparison of the CS simulation of the streamflow hydrograph and the observed hydrograph for the calibration period (2012–2015).

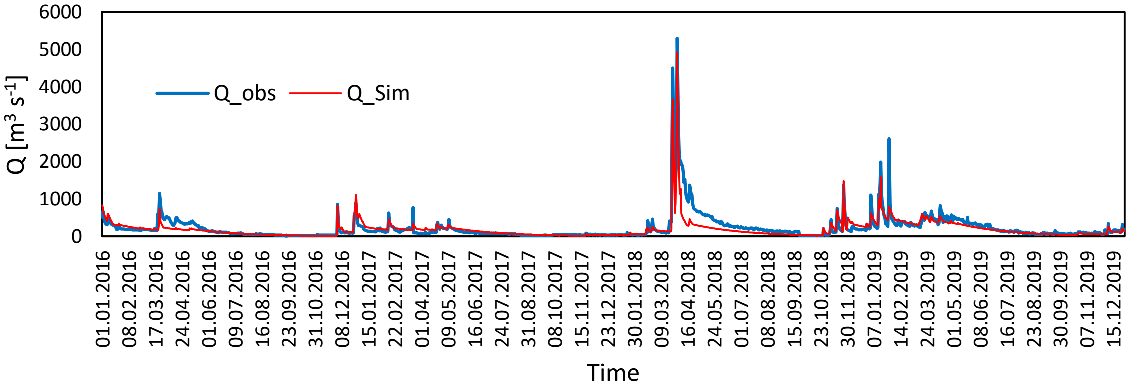

Fig. 5. Comparison of the CS simulation of the streamflow hydrograph and the observed hydrograph for the validation period (2016–2019).

Table 3. Maximum variations of the NSE index due to sensitivity analysis of the parameters

No	Parameter	Maximum variations of NSE index [%]	No	Parameter	Maximum variations of NSE index [%]
1	maxbas	20.4	8	ddf	16.9
2	scf	19	9	Ts	7.4
3	K2	17.8	10	Tm	13.5
4	K1	19.5	11	Tr	14
5	K0	14.1	12	L	21.6
6	LP	12.3	13	BETA	18.8
7	perc	15.3	14	Fc	10.8

Table 4. Goodness-of-fit measures for CS and EB modeling of streamflow hydrograph during calibration period

Streamflow events	Continuous			Event-based		
	NSE	NRMSE	MAPE	NSE	NRMSE	MAPE
Event 1	0.98	0.09	11.1	0.95	0.181	16.2
Event 2	0.98	0.11	12.5	0.94	0.19	25.9
Event 3	0.88	0.18	22.1	0.98	0.08	8.8
Event 4	0.85	0.41	24.1	0.86	0.39	22.5
Event 5	0.97	0.187	13.2	0.92	0.32	43.1

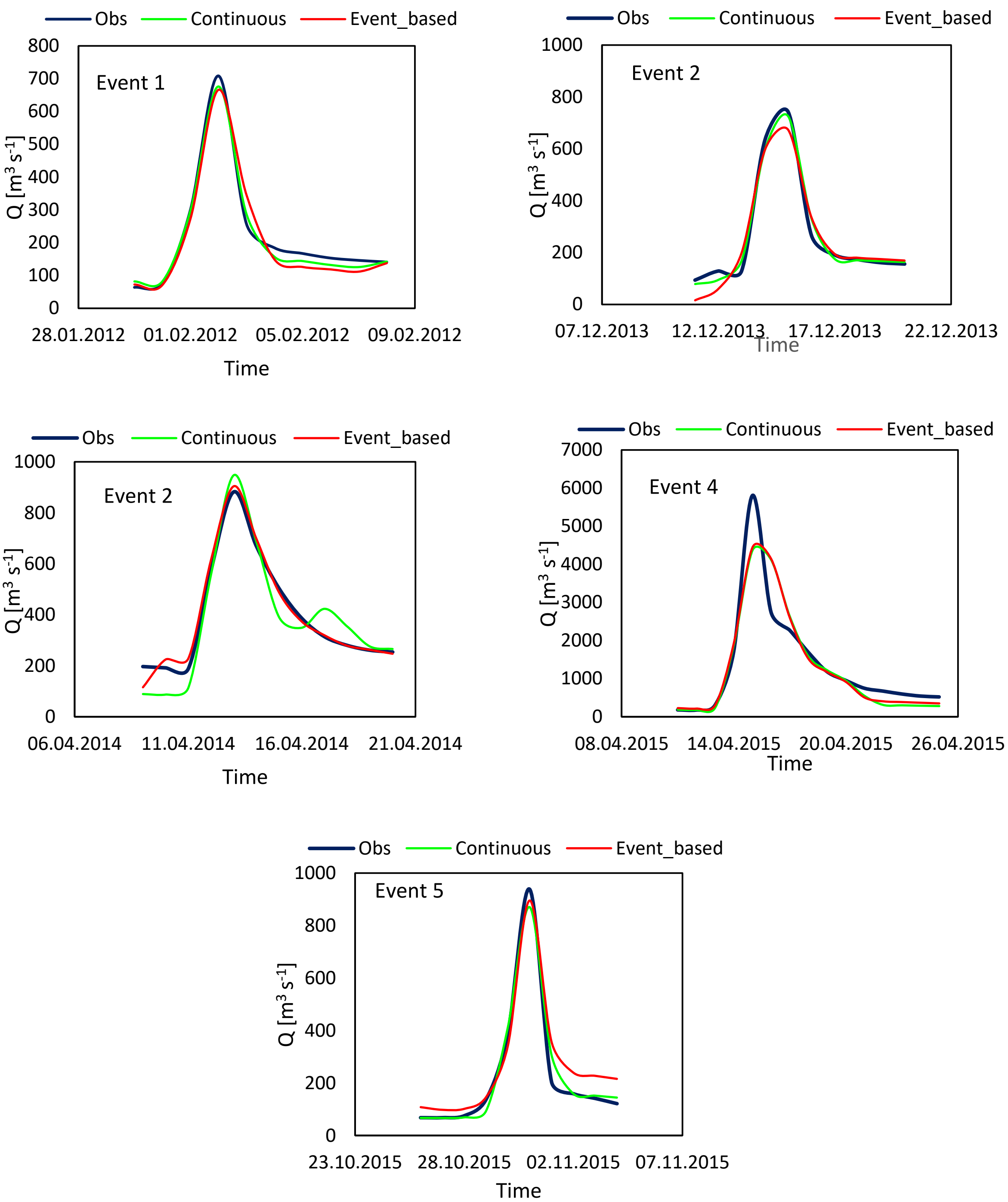

Fig. 6. Comparison of the CS and EB modeling of streamflow hydrograph during calibration period.

Table 5. Goodness-of-fit measures for CS and EB modeling of streamflow hydrograph during validation period

Streamflow events	Continuous			Event-based		
	NSE	NRMSE	MAPE	NSE	NRMSE	MAPE
Event 6	0.94	0.28	41.3	0.83	0.39	114.9
Event 7	0.77	0.21	23.4	0.72	0.23	26.6
Event 8	0.83	0.31	21.7	0.81	0.33	28.1
Event 9	0.76	0.32	30.1	0.87	0.23	28.9

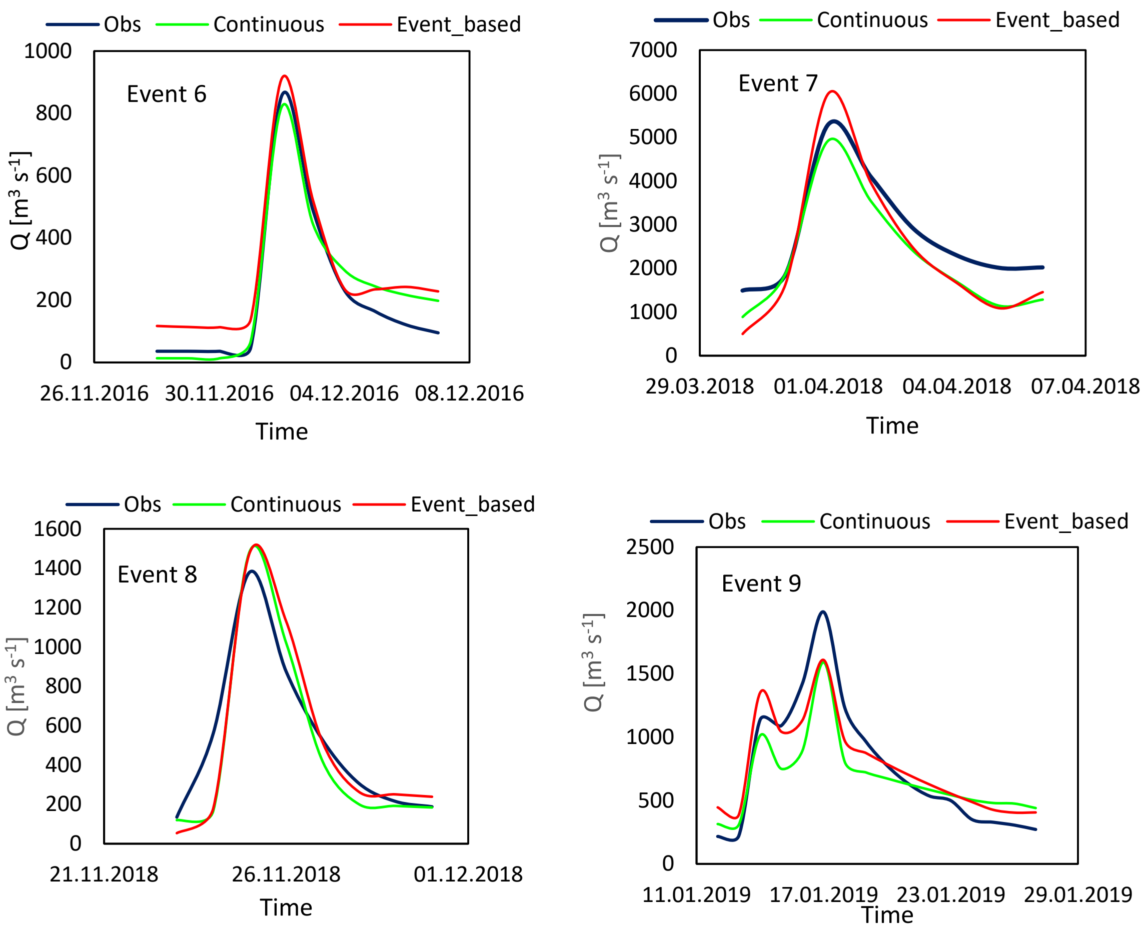

Fig. 7. Comparison of the CS and EB modeling of streamflow hydrograph during validation period.

Conclusion

This study compares the CS and EB simulations of streamflow hydrographs using the HBV model in the Dez River Basin. The results illustrated that the average values of the NSE index for CS and even-based simulation of streamflow respectively were obtained 0.83 and 0.8 in the validation stage. Besides, the average values of error for mentioned modelling approaches were estimated 0.28 and 0.3, respectively. Therefore, it can be concluded that the HBV model has an efficient performance for CS and EB modeling of streamflow hydrographs. However, the model performs slightly better for continues simulation of streamflow in comparison with EB modeling. Evaluation of the results showed that the most sensitive parameters were L, maxbas, K1, scf, and BETA to simulate streamflow in calibration period. Generally, the hydrological modeling used in this research facilitates subsequent hydrological studies in this basin. The results of this study is critical for flood warning and prediction in the next studies.

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