Flood hydrograph prediction in a semiarid mountain catchment: The role of catchment subdivision

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Abstract
The effect of different degrees of catchment subdivision coupled with the nonlinear storage–discharge relationship on hydrograph prediction is evaluated in a mesoscale catchment in the Zagros mountain region, southwest of Iran. The catchment is divided into different sets of subcatchments based on catchment geomorphology, and runoff hydrographs are simulated for each set using a network-based runoff routing model, watershed-bounded network model. It is shown that, in the absence of fully distributed data, if a semidistribution of storage–discharge is taken into consideration in the modeling process, lumped rainfall data could provide valuable information on the hydrological response of catchment in data-scarce regions, which are usually found in remote areas, such as mountains. Although the results suggest that catchment subdivision leads to more accurate results, a subcatchment area threshold of about 3% of the catchment extent is found. Below this, no further improvement in simulation accuracy can be achieved, probably because of the limitations of the data interpolation method used by the model.

KEYWORDS
catchment subdivision, flood routing, hydrograph simulation, lumped rainfall data, storage–discharge, Zagros

1 | INTRODUCTION

Flood hydrograph prediction in ungauged catchments is supported by several decades of research experience (e.g., Gargouri-Ellouze & Eslamian, 2014; Ghasemizade, Mohammadi, & Eslamian, 2011; Gotzinger & Bardossy, 2007; Hirsch, 1979; Hisdal & Tveito, 1992; Hrachowitz et al., 2013; Kokkonen, Jakeman, Young, & Koivusalo, 2003; Komi, Neal, Mark, Trigg, & Diekkrüger, 2017; Loukas & Vasiliades, 2014; Merz & Bloschl, 2004; Nathan & McMahon, 1990; Oudin, Kay, Andreassian, & Perrin, 2010; Parajka et al., 2013; Patil & Stieglitz, 2012; Pilgrim, 1983; Post & Jakeman, 1996; Razavi & Coulibaly, 2013; Rezaei-Sadr, 2019). However, most results are obtained from developed parts of the world. In such countries, during the last few decades, there has been a tendency toward the application of distributed models rather than simple lumped models, because of increased availability of distributed information obtained thanks to advances in modern satellites and radars technologies as well as advances in ground-based observation technologies. Moreover, since most experiences were based on methods rooted in empiricism or data-calibration based techniques (Hrachowitz et al., 2013), applying the obtained results for new locations in different environments is subjected to high degrees of uncertainty due to the problems related to calibration, regionalization, and localization. For this reason, hydrological and environmental prediction worldwide is confronting a...
big scientific and technologic gap between developed and developing regions of the world. For example, most Iranian catchments that are exposed to high risk of flooding are still ungauged, and the task of catchment response prediction in these regions is highly limited to the calibration and regionalization of simple lumped models for computing runoff volume soil conservation service-curve number (e.g., SCS-CN method) and peak discharge (e.g., rational method) (Rezaei-Sadr, 2015, 2017). Although the application of such simple models for water resources planning can be justifiable to some extent, more information on the storage-discharge relationship is required for flood hydrograph prediction in ungauged catchments. In the absence of fully distributed data, an efficient way to obtain an overall understanding of the hydrological response of catchment, at a level between a simple lumped system and the fully distributed approach, could be dividing the catchment into a number of partitions with the aim of taking into consideration the spatial nature of surface storage and runoff throughout the catchment.

Catchment subdivision is often used in semidistributed models to minimize the effect of spatial heterogeneities in soils and land cover across the catchment in order to better explain the hydrologic response of the catchment under study. This is because catchment topographic features are highly controlled by catchment extent. Different patterns of stream network connection and hillslope size can lead to completely different runoff production on hillslopes and in stream channels (Zhang, Wang, Wang, Li, & Wang, 2013). For these reasons, the level of detail in geomorphological characteristics defining the catchment under study can have the potential to alter the outputs of the model leading to more accurate results. During the last two decades, several studies have been carried out using different models to study the influence of subcatchment size on the rainfall-runoff process (Ao et al., 2003; Chen, Xie, & Chen, 2011; Cleveland, Luong, & Thompson, 2009; Ghosh & Hellweger, 2011; Kumar & Merwade, 2009; Muleta, Nicklow, & Bekele, 2007; Tripathi, Raghuwanshi, & Rao, 2006). Although there is a scientific consensus about the importance of choosing an appropriate catchment partitioning degree, the results reported in the literature is quite different. For example, while Muleta et al. (2007) concluded that larger subcatchment could decrease flood peak discharge, Cleveland et al. (2009) and Chen et al. (2011) reported that the effect of catchment subdivision on peak flow magnitudes can be ignored. Meanwhile, some other researchers reported contradictory results on the relationship between subcatchment size and runoff discharge (Ao et al., 2003; Ghosh & Hellweger, 2011; Kumar & Merwade, 2009). Most of these studies have only focused on how catchment subdivision affects runoff volume and peak discharge. However, the effect of catchment subdivision on runoff hydrograph prediction, which is an important concern in flood studies, has not yet been well studied.

This study investigates the effect of catchment partitioning into different degrees of subdivisions on flood hydrograph prediction via an event-based semidistributed network runoff routing model, watershed-bounded network model (WBNM). The emphasis will be mainly on timing and the rising limb of hydrograph, which are considered the most influential factors in flood forecasting systems. From this point of view, this study aims to improve the ability of flood hydrograph prediction in a remote area where the spatial information of runoff is very limited due to poor gauge arrangement, and hence, the calibration process of rainfall-runoff models is difficult or perhaps impossible. This study is also aimed at improving the knowledge about the minimum subbasin area threshold to increase the accuracy of flood prediction in semiarid mountain regions where only lumped data are available.

2 | STUDY CATCHMENT AND DATA

The study area is a meso-scale catchment, Roodzard (868 km²), in the southwestern parts of the Zagros mountain region, Iran (Figure 1). The climate of the region is divided into two separate climatic phases including hot-dry summers and mild winters as predominant weather conditions. The catchment is characterized by high spatial variability in terms of topography, land use (cover), and rainfall patterns. A distinct pattern of increasing elevation from 345 to 3,300 m is observed from southwest to northeast along with increasing rainfall and decreasing temperature patterns throughout the area. The mean annual precipitation of approximately 580 mm occurs mostly in the winter and rainy seasons (Rezaei-Sadr, 2012; Rezaei-Sadr, 2015; Rezaei-Sadr, Akhoond-Ali, Radmanesh, & Parham, 2012; Rezaei-Sadr & Sharifi, 2018). The catchment is extended between deep alluvial deposits mainly covered by a high percentage of pasture and farmlands in southwestern lowlands and steep mountains covered by shallow soils and pasture and woods–grass–range combination in northeastern highlands (Zarei, 2012). The catchment is equipped with one autorecording water level gauge at the outlet and several recording rain gauges located inside the catchment and adjacent areas, all operating under the supervision of Khuzestan Water and Power Authority, Ahvaz, Iran.

Orography plays a decisive role in forming strong convective instability situations throughout the region. It forces the air masses to ascend upward and form more than one local rainfall systems. These systems have high spatial variability, and their spatial scales are usually lower than the catchment scales (Rezaei-Sadr, 2012). Therefore, to account for the spatial variability of rainfall, only extensive rainfall events that
were recorded simultaneously in four or more rain gage stations within and adjacent to the catchment were selected as the study storms. For this reason, the number of selectable rainfall-runoff events was limited. Only 13 rainfall hyetographs of 15-min time intervals and their corresponding runoff hydrographs which occurred between 1991 to 2004 were selected for the analysis.

3 | METHODS

3.1 | Model description

Runoff-routing techniques are useful alternative tools for simple lumped models to explain the more precise response of catchment especially for flood hydrograph simulation. Several different runoff routing models are used in hydrology. Runoff routing model (RORB), WBNM, storm water management model (SWMM), and ILSAX urban storm water drainage design and analysis program (ILSAX) are examples of such models. RORB and WBNM are network models with relatively similar structures, although the latter is based on more detailed consideration of catchment geomorphology (Pilgrim, 2001). In network models, the storages are arranged to represent the stream network of the catchment (Bodhinayake, 2004). The distributed nature of the storage is represented by a separate series of storages for the stream and its tributaries. This provides a degree of physical realism (Boyd & Cordery, 1989). The main difference between RORB and WBNM is that the latter has two different types of storage, ordered and interbasin. Therefore, as the storage characteristics and delay times of these two types of subcatchments are different, the provision of these two types of storage is physically realistic (Boyd, Rigby, & Van Drie, 1996). SWMM is used for runoff routing purposes in natural catchments. However, it is mainly used for both single event and long term simulations of runoff quality and quantity in urban areas. It has been used for analysis and planning of drainage networks throughout the world with the emphasis on urban storm runoff and sanitary sewers (Gironás, Roesner, & Davis, 2009). ILSAX is also a runoff routing model that was established based on Time-Area method. It is also a network model that needs general

FIGURE 1 Geographical location of the Roodzard catchment, Iran
inputs like catchment characteristics and travel time (Thosainge, 2000).

WBNM proposed by Boyd, Pilgrim, and Cordery (1979) is a network runoff-routing model which represents the semi-distributed nature of the water storage throughout the catchment by a series of storage areas (Boyd, 1985). The model maintains a good relationship between the distributed nature of the storage and the catchment geomorphological aspects, which enhance the ability of the model to simulate flood hydrograph in comparison with simple lumped models (Pilgrim, 2001). The model has been tested and validated in areas ranging from 0.1 to 8,000 km² (Bodhinayake, 2004; Boyd et al., 1996; Boyd & Cordery, 1989; Rezaei-Sadr, 2012, 2019; Rezaei-Sadr et al., 2012). The main weakness of the model is that the power function of nonlinear measurement may not be correct for large floods in natural catchments, when linearity may be approximated. In this case, major floods may be overestimated if nonlinear runoff routing is applied. In the following sections, the background of the model is described.

3.1 Dividing catchment into subcatchments

The catchment is divided into several subcatchments on the basis of river network and topography, each one is restricted by its ridge. Guidelines for catchment subdivision are given by Boyd (1985).

3.1.1 Modeling rainfall

WBNM uses a recorded hyetograph at one or several rain gages. The time step of hyetograph is set by the user to suit the storm. The hyetograph of each subcatchment is constructed on the basis of the temporal pattern of rainfall in the nearest rain gage. Moreover, the average intensity of rainfall is calculated using surrounding rain gage weights from the subcatchment on the basis of inverse distance weighting concept (Boyd et al., 1996). Spatial variations of rainfall can be modeled using several rain gages. For each subcatchment, the hyetograph is calculated by Thiessen or inverse distance weighting methods. Then, using an appropriate loss model, the subcatchment hyetograph is converted to rainfall-excess hyetograph.

3.1.2 Modeling catchment

The rainfall excess is transformed into runoff and routed to the outlet, forming the hydrograph at the outlet of each subcatchment. The overland flow on each subcatchment is modeled by the lag relation. There are two types of subcatchments, ordered and interbasin. The first type of subcatchments is located at the upper end of stream network, receives rainfall on the surface, and converts it via overland flow into runoff hydrograph at the outlet (Boyd et al., 1996). The second type of subcatchments receives both runoffs from upstream subcatchments and rain falling on the surface simultaneously. The rainfall is transformed to overland flow, joins the upstream runoff, routes through the channel system, and finally forms the runoff hydrograph (Boyd et al., 1996). A nonlinear storage-discharge relationship is used in the runoff routing calculations.

3.2 Model evaluation techniques

In this study, the model’s ability to simulate runoff hydrographs is evaluated by several commonly used, accepted, and recommended techniques, Nash–Sutcliffe efficiency (NSE) index (Nash & Sutcliffe, 1970) and Kling–Gupta efficiency (KGE) (Gupta, Kling, Yilmaz, & Martinez, 2009; Kling, Fuchs, & Paulin, 2012) as dimensionless indexes, RMSE-observations SD ratio (RSR) (Singh, Knapp, & Demissie, 2004) and percent error (E½) as error indexes, and graphical comparison as a graphical technique.

NSE is a commonly used objective function to evaluate the overall fit of simulated hydrograph to observed hydrograph (Gupta et al., 2009; Guse et al., 2017; Kling et al., 2012; Pfannerstill, Guse, & Fohrer, 2014; Sevat & Dezetter, 1991). NSE changes between −∞ and 1.0, but the optimal value is 1.0. Although NSE values between 0 and 1.0 are considered as the acceptable level of performance (Nash & Sutcliffe, 1970), for streamflow records, model simulation results can be evaluated as satisfactory when NSE values are only more than 0.5. (Moriasi et al., 2007). NSE is calculated by

\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (y_{i}^{\text{obs}} - y_{i}^{\text{sim}})^2}{\sum_{i=1}^{n} (y_{i}^{\text{obs}} - y_{i}^{\text{mean}})^2}
\]

where \(y_{i}^{\text{sim}}\) and \(y_{i}^{\text{obs}}\) are observed and simulated values and \(y_{i}^{\text{mean}}\) is the mean of observations.

On the basis of decomposition of NSE into three components, the KGE criterion was developed (Gupta et al., 2009; Kling et al., 2012) as follows:

\[
\text{KGE} = 1 - \sqrt{(\alpha - 1)^2 + (\beta - 1)^2 + (r - 1)^2}
\]

\[
\alpha = \frac{\sigma_s}{\sigma_y},
\]

\[
\beta = \frac{\mu_s}{\mu_y},
\]

where \(\sigma_s\) and \(\sigma_y\) are SDs of simulated and observed data, \(\mu_s\) and \(\mu_y\) are average values of simulated and observed data, and \(r\) is correlation coefficient. Using this index, model
errors are related to variability, bias, and correlation between observed and simulated discharge data. Alpha is the variability ratio between the SD of simulated and observed data. An alpha value larger than 1 indicates that variability in simulated discharge data is higher than in observed data, while alpha lower than 1 represents the opposite case. Beta is the bias ratio between average values for simulated and observed discharge data. Beta larger than 1 shows a positive bias and indicates an overestimation of discharge, while beta values lower than 1 represent an underestimation. The correlation coefficient is used to evaluate the temporal agreement between simulated and observed data. All the three above-mentioned components and also KGE have an ideal value of 1. These three components create the Euclidean distance to the ideal point in the 3-D criteria space (Gupta et al., 2009).

RSR was first proposed by Singh et al. (2004) to incorporate an error index and the additional information recommended by Legates and McCabe (1999). This index is calculated as the ratio of the root mean square error root mean square error (RMSE) and the SD of observed data (STDEV$_{obs}$), as follows:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \sqrt{\frac{\sum_{i=1}^{n} (y_{i}^{obs} - y_{i}^{sim})^2}{\sum_{i=1}^{n} (y_{i}^{obs} - y_{\text{mean}})^2}}$$

(3)

Among other factors, the prediction of time-to-peak is also very important in flood mitigation purposes. One of the model evaluation statistics for time-to-peak recommended by ASCE (1993) is simple percent error computed by dividing the difference between the observed and simulated time-to-peak by the observed time-to-peak and expressing the result as a percentage (Beven & Kirkby, 1993)

$$E_T = 100 \times \left( \frac{T_{obs}^{p} - T_{sim}^{p}}{T_{obs}^{p}} \right)$$

(4)

where $T_{obs}^{p}$ and $T_{sim}^{p}$ are observed and simulated time-to-peak, respectively.

FIGURE 2 Different degrees of catchment subdivisions based on catchment geomorphology: (a) 4 subcatchments, (b) 10 subcatchments, (c) 14 subcatchments, (d) 19 subcatchments, (e) 28 subcatchments, and (f) 37 subcatchments
RESULTS AND DISCUSSION

4.1 Catchment partitioning into subcatchments

In order to simulate catchment behavior influenced by different degrees of catchment subdivision, the catchment under study was divided into different subareas based on catchment geomorphology. Using the digital elevation model shown in Figure 1, the mainstream and the major tributaries are identified, and the ridge of subareas are drawn for different degrees of catchment subdivisions. Therefore, different degrees of catchment subdivisions including 4, 10, 14, 19, 28, and 37 subcatchments are provided (Figure 2). At first, it was supposed to have some sets of subcatchments with relatively uniform intervals. Therefore, some hypothetical sets of subcatchment were considered and the catchment was divided into subcatchments based on a threshold of minimum subcatchment area corresponding to these sets of subcatchment. However, the geomorphological characteristics of the catchment under study force to consider one or more additional subcatchment. For example, for the Roodzard catchment, the connection point of the four substreams to the mainstream was very close, and therefore, considering one extra subcatchment in this location was inevitable. As subcatchment numbers increase, this feature becomes more intense. For this reason, the intervals between subcatchment numbers are not distributed uniformly. Each subarea is bounded by the ridgeline, forms a catchment within the larger catchment, and routes excess rainfall to produce a flood hydrograph at the outlet. The average areas of subcatchments are shown in Table 1.

4.2 Model calibration and validation

WBNM in its original form uses the value of $\rho = 0.77$ as an overall value of nonlinearity measurement for Australian catchments. However, it can be changed for catchments in different climates and regions under strong pieces of evidence (Boyd et al., 1979). Rezaei-Sadr et al. (2012); in the study on the linear–nonlinear behavior of the rainfall-runoff process, the model was calibrated and a new nonlinear power function was proposed ($m = 0.61$) for the Zagros mountain region, in southwest of Iran. In this study, this new power function is calibrated for the study catchment. Totally 13 rainfall events along with their corresponding runoff hydrographs were used. The characteristics of the selected rainfall events for calibration and validation phases are shown in Table 2. It is quite evident that both sets of rainfall events which are used for calibration, and validation phases are statistically similar.

For the calibration phase, 10 events were selected, and runoff hydrographs were simulated by the model using new proposed and default power values ($m$) as nonlinearity measurements. The simulated hydrographs were then compared with observed hydrographs using NSE index. It was found that the best hydrograph simulations for the study region were obtained from the power value of $m = 0.61$. The overall comparison between the proposed power $m$ value and the default value of the model ($m = 0.77$) is shown in Table 3.

Applying the new calibrated nonlinear power function ($m = 0.61$), the model was then validated for the study region using three other rainfall events that were not used in the calibration phase. The percent error ($E_T$) of simulated

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**Table 1** Different levels of catchment subdivisions used in the study

| Level of catchment partitioning | No. of subcatchments |
|-------------------------------|----------------------|
|                               | 4   | 10 | 14 | 19 | 28 | 37 |
| Average area of subcatchments ($A_i$) (km²) | 217.1 | 86.8 | 62.0 | 45.7 | 30.7 | 23.5 |
| $A_i$/Total area | 0.25 | 0.10 | 0.071 | 0.053 | 0.035 | 0.027 |

**Table 2** Characteristics of selected rainfall events used in calibration and validation phases

| Phase | No. of events | Ave. rainfall depth (mm) | Ave. intensity (mm/hr) | Ave. duration (hr) | Ave. peak discharge (m³/s) | Ave. time to peak (hr) |
|-------|---------------|--------------------------|-----------------------|-------------------|---------------------------|-----------------------|
| Calibration | 10            | 44.3                     | 2.8                   | 14.9              | 210.2                     | 11.5                  |
| Validation | 3             | 38.7                     | 3.1                   | 13.0              | 213.1                     | 12.1                  |

**Table 3** Nash–Sutcliffe efficiency (NSE) values for the proposed and default $m$ values (columns 2 and 3) and the percent error for peak discharge ($Q_p$) and time-to-peak in the validation phase (columns 4 and 5)

| Catchment   | $m = 0.61$ | $m = 0.77$ | $Q_p$ (%) | $E_T$ (%) |
|-------------|------------|------------|-----------|-----------|
| Abolabbas   | 0.656      | 0.600      | 3.2       | 0.9       |
| Roodzard    | 0.771      | 0.675      | 4.4       | 2.7       |
| Allah       | 0.645      | 0.545      | 3.4       | 1.3       |
| Ave         | 0.691      | 0.607      | 3.7       | 1.6       |
peak discharges (m$^3$/s) and time-to-peaks (hr) are also shown in Table 3. The overall fit of simulated hydrographs to observed hydrographs for two rainfall events used in the validation phase are shown in Figure 3. On the basis of the above-mentioned results, the nonlinear power value of $m = 0.61$ is adopted and used in this study.

4.3 | Hydrograph evaluation

To simulate the response of a catchment to a single rainfall event, Boyle, Gupta, and Sorooshian (2000) proposed that the hydrograph should be better divided into different phases including rising limb, falling limb, and base-flow based on differing catchment behavior. In flood prediction and mitigation works, especially in mountain regions, hydrograph characteristics from the beginning to peak flow (rising limb and time-to-peak) play a significant role, because this information provides useful tools for engineers and managers to establish a real-time warning system in order to decrease the hazardous consequences of floods.

Rainfall hyetographs recorded in the rain gauge station are distributed over the catchment on the basis of the inverse distance weight between the center of each subcatchment and the rain gauge station. Then, the hyetograph is transformed to runoff which forms the runoff hydrograph at the outlet. The ability of the model is evaluated in the subsequent sections.

4.3.1 | Graphical evaluation of simulated hydrographs

A preliminary insight into the model performance can be gained by graphical techniques. One commonly used graphical technique, hydrograph comparison, helps to identify the overall fit of observed and simulated hydrographs comprising the model bias, the shape of the rising and recession limbs, differences in timing, and also the magnitude of peak discharges (ASCE, 1993; Moriasi et al., 2007).

In the first step of the analysis, the rising limb of simulated hydrographs is plotted against the corresponding observed hydrographs at the catchment outlet for different catchment subdivisions. In Figures 4–6, the comparisons are shown for three typical rainfall events used in the study. It is clear that, when the catchment is considered as a fully lumped area, the model bias is very considerable in the terms of both the shaping and timing of the simulated hydrographs. However, by dividing the catchment into different degrees of subcatchments, the model bias decreases gradually and both the rising limbs of hydrographs and time-to-peaks are simulated more accurately. Therefore, the best model performance is obtained for more catchment subdivisions.

4.3.2 | Evaluation the rising limb of simulated hydrographs

For each rainfall event, the response of the catchment is simulated for different numbers of catchment subdivisions. Then, the simulated hydrographs are compared with observed hydrographs using different performance statistics. According to NSE values (Figure 7), when the catchment is considered as a fully lumped area, the model cannot reproduce the hydrological response of the catchment correctly. Six out of 13 NSE values are not in the acceptable range (below zero) and the others are very low (below or equal 0.5) meaning that the simulated hydrographs do not match the observed hydrographs sufficiently. For the four subcatchments cases, most NSE values are also not acceptable although the results are relatively better than the fully lumped condition. However, by increasing the number of subcatchments, the NSE values increase considerably. For the cases of 10 and 14 subcatchments, 9 out of 13 NSE values are acceptable (more than 0.5) showing much better...
FIGURE 4  Comparison between the rising limbs of simulated hydrographs (dashed line) and observed hydrographs (bold line) for different catchment subdivisions for the rainfall event of November 15, 1984
FIGURE 5  Comparison between the rising limbs of simulated hydrographs (dashed line) and observed hydrographs (bold line) for different catchment subdivisions for the rainfall event of December 10, 1991
Figure 6  Comparison between the rising limbs of simulated hydrographs (dash line) and observed hydrographs (bold line) for different catchment subdivisions for the rainfall event of March 12, 1994.
results in comparison with the two previous cases. A significant better condition can be seen for the case of 19 subcatchments so that all NSE values are in the acceptable range, often more than 0.80. Finally, for the cases of 28 and 37 subcatchments, the best model performance is obtained since 12 out of 13 NSE values are more than 0.90, with the average values of 0.916 and 0.934, respectively, highlighting a very good match between the simulated and observed hydrographs.

The values of KGE for all rainfall events in the calibration phase are shown in Figure 8. Although all KGE values are positive and have lower variability for the different numbers of subcatchments in comparison with NSE values, the same trend can be observed. Obviously, by increasing the number of subcatchments, KGE shows a tendency toward the ideal value of 1. This supports the above-mentioned findings for NSE. The average NSE and KGE values are plotted against the number of subcatchments in Figure 9. As it is shown, at first, both NSE and KGE increase significantly from fully lumped condition to less than 10 subcatchments. Then, the slope of the graph changes abruptly becomes gentle with no tendency to approach a constant value. This graph also suggests the minimum number of subdivisions for the study catchment is 10.

RSR values shown in Figure 7 also support the above-mentioned findings. The RSR values show the weak
performance of the model for the fully lumped condition and also the low number of catchment subdivisions. However, similar to NSE and KGE, the model ability to reproduce catchment behavior is improved with increasing the number of subcatchments. In Figure 9, the variation of average RSR values versus the number of catchment subdivisions is shown. The graph shows an abrupt change point in the first quadrant which divides it into two distinct segments. The change point happens for about 10 subcatchments, since the steep slope of the graph is changed and becomes gentle. After that, RSR decreases gradually as the number of subcatchments increases and approaches a nearly constant value for more than 30 subcatchments, and again the best model performance is achieved for 37 subcatchments.

### 4.3.3 | Time-to-peak evaluation

Time-to-peak plays a significant role in operational flood forecasting, especially in mountain regions, where the hydrological response of catchments is very rapid. The effect of catchment subdivision on the ability of the model to simulate time-to-peak is evaluated and results are shown in Figures 8 and 9. The simple percent error ($E_T$) computed for all simulated hydrographs (Figure 8) shows that more detailed storage–discharge distribution through catchment partitioning could improve the model's ability to estimate time-to-peak more accurately. According to Figure 9, which shows the variation of average $E_T$ values versus the number of subcatchments, the best simulation is obtained for
37 subcatchments with the average $E_T$ value of 3.6%, slightly better than 3.9% which is obtained for 28 subcatchments ($E_T$ values are not expressed as percent in the graph). However, the difference is not important, since the slope of the graph becomes very gentle showing a tendency toward a constant value. Therefore, both 28 and 37 subcatchment numbers could be assigned as the reliable number of catchment partitioning in order to provide sufficient information about flood timing. On the other hand, for the lower numbers of subcatchment, the error increases and the worst result is obtained for the fully lumped condition with averagely 35.1% error. According to Figure 8, for all the cases, the positive value of $E_T$ means that the simulated time-to-peaks occur before the observed time-to-peaks. However, from fully lumped condition to 37 subcatchments, the error is decreased considerably, and for some rainfall events, it becomes zero.

The results clearly highlight the important role of catchment subdivisions level on runoff prediction which can be attributed to the catchment geomorphology. During the transformation of rainfall into hydrographs, a portion of rainfall can be lost by evapotranspiration and deep percolation, the remainder is added to water content which is already stored on the surface, causing the overland flow formation. Overland flow is received and collected by channel network from the hillslopes, delivered to the outlet. At this stage, both storing water and delaying occur (Beven & Kirkby, 1993). In small catchments, the longest delay happens in hillslopes, but for larger catchments (50 km$^2$ or larger), travel time through the channel network plays an important role, and usually, it becomes dominant in shaping and timing the outlet hydrograph (Beven & Kirkby, 1993). When the catchment is considered as a fully lumped area, it means that a shorter length of channel network is taken into consideration by the model. For this reason, in the simulation process, the overland flow becomes prevailed and the fraction of channel flow becomes less causing the delay effect of channel network on travel time to be decreased. Accordingly, the simulated hydrograph reaches the peak flow much faster than the observed hydrograph (Figures 4–6). On the other hand, by increasing the number of subcatchments, the length of the channel network and the fraction of channel flow is increased, and the travel time is increased. Under these circumstances, the delay effect of channel network on runoff hydrograph is highlighted in the simulation process, and therefore, a portion of water is stored temporarily in the channel network which receives at the outlet with delay. This means that the stored water in the channel network is released slowly at the outlet, similar to what really happens in the catchment. Thus, similar to observed hydrograph, the slope of the rising limb of simulated hydrograph becomes relatively gentle and reaches the peak with a delay, and the difference between the time-to-peak of simulated and observed hydrographs is decreased as can be seen in Figures 4–6 for the case of 37 subcatchments. For this reason, catchment partitioning into more subdivisions could lead to more accurate hydrograph simulation which is very essential in flood studies. Consequently, the runoff routing process will be much more accurate and a more realistic physical description of catchment response will be obtained. On the contrary, taking into consideration the catchment as the fully lumped area could not provide the accurate prediction of runoff hydrograph because simplifications based on lumped condition cause important deviations from the reality and cannot successfully reproduce catchment response.

Although it can easily be hypothesized that as the number of subcatchments increase, the model performance also increases, it should be noted that there will always be a compromise between model complexity and model performance. It is argued that complex models with the high number of parameters can better simulate the response of catchment over the calibration phase, but they face the limitation of overparameterization in the validation phase (Beven, 1989; Orth, Staudinger, Seneviratne, Seibert, & Zappa, 2015). On the contrary, simple models with few parameters usually cannot simulate runoff with sufficient precision during the calibration phase but they can show a good performance in the validation phase (Holländer et al., 2009; Perrin, Michel, & Andreassian, 2001). Moreover, in the case of scattered or uncertain input data, it is debated that simple (lumped) models may challenge complex models (Beven, 1989, Orth et al., 2015). For the meso-scale Roodzard catchment, it seems that a semidistribution approach of storage–discharge relationship at a level between lumped and distributed approaches, coupled with lumped data, can provide satisfactory results in comparison with fully lumped approach. It is clearly shown that the more distribution of storage–discharge caused by catchment partitioning could result in
the better performance of the model. In other words, the more the storage–discharge distribution, the more accurate the simulation of runoff hydrograph. However, it is important to note that, all evaluation techniques used in the study show a little difference between the results obtained from 28 and 37 subcatchments. As shown in Figure 9, it can be concluded that the results of the model evaluation indexes will not be changed considerably for more than 37 subcatchments. Since the related graphs are approaching stable values with increasing the number of subcatchments, no more precise hydrograph simulation is expected for more catchment subdivision. This suggests a subcatchment area threshold of 27.5 km², nearly 3% of the catchment area, for the study region below which no important improvement in hydrograph prediction can be achieved when converting lumped rainfall data into semidistributed data. This is probably due to the inherent constraints of the methods used by the model for the interpolation and extrapolation of rainfall data. Therefore, it can be concluded that in the absence of distributed rainfall, discharge and soil wetness data, a semi-distribution of storage–discharge relationship, can easily improve the knowledge of runoff producing mechanism which helps flood prediction and mitigation throughout the region. This approach may be beneficial, because in the case of scattered or uncertain input data and for some applications like risk analysis and forecasting, the performance of simple models may be treated as a benchmark for complex models (Gurtz et al., 2003; Kobierska et al., 2013; Perrin et al., 2001).

5 | CONCLUSIONS

In order to better understand the catchment response in a mountain region, the influence of catchment partitioning on the storage–discharge relationship is evaluated using a network-based runoff routing model, WBNM. Based on geomorphological features, the model has the ability to distribute a lumped rainfall hyetograph over the subcatchments. The study area, Roodzard meso-scale catchment, is located in the Zagros mountain region in the southwest of Iran. Thirteen rainfall events with wide spatial coverage that were recorded simultaneously in four or more rain gage stations are used to simulate the catchment response. Different degrees of catchment subdivision including 4, 10, 14, 19, 28, and 37 subcatchments are used and runoff hydrographs corresponding to rainfall events are simulated and compared with observed hydrographs in terms of rising limb and time-to-peak.

The ability of the model to reproduce the rising limb of hydrographs are evaluated by three widely used and accepted model evaluation techniques, NSE and KGE as dimensionless indexes and RSR as an error index. The findings show that considering the catchment as a fully lumped area does not provide the accurate simulation of catchment response. However, dividing the catchment into a number of subcatchments improves the model's ability to simulate outlet hydrographs. For more than 20 subcatchments, the simulated hydrographs match the observed hydrographs sufficiently, and the best results are obtained for 37 subcatchments with fairly perfect match between simulated and observed hydrographs. On the other hand, the worst simulation results are achieved when the catchment under study is considered as a fully lumped area. Under this condition, all simulated time-to-peaks positively deviate from the observed time-to-peaks with the average error of 35.1%. From the practical point of view, the findings of this study can be valuable for informing hydrological modeling studies for flood risk management in arid and semiarid mountain catchments. Because of the lack of sufficient natural vegetation on the ground and also steep topography, the hydrological response of these catchments is very fast causing these areas to be very prone to severe floods. Therefore, establishing a real-time river flow forecasting system in these regions is very important in order to better control the hazardous consequences of floods. The experience of deadly floods happened in March and April 2019 in the mountain regions of Iran has revealed this reality that establishing such warning systems are very urgent. Two key characteristics of flood hydrograph that play an important role in a flood warning system are the rising limb and time-to-peak. Modeling these two factors could be the baseline for future flood mitigation projects. The results show that dividing the catchment into subdivision could help to model these two factors, providing initial information for the engineers and managers to make accurate decisions in flood defense operations, such as evacuating rural and urban areas, protecting hydraulic structures, such as dams, canals, and pump stations, and also other infrastructures.

It is concluded that, in the absence of fully distributed data, the semidistribution of lumped rainfall data calculated by the inverse distance weights between each subcatchment and the rain gauge station provide appropriate simulations in comparison with the fully lumped condition. However, it is proved that although the higher number of catchment subdivision theoretically leads to the more accurate simulation of flood hydrograph, the model cannot provide more accurate results for more than 37 subcatchments because of the limitations of the data interpolation method used by the model.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.
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