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Probability Distributions and Return Periods of Extreme Rainfall Events in the Zagros Mountains: Karkheh Basin Floods

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Abstract

This study investigates the return period of heavy rainfall events in the Zagros Mountains of Iran, focusing on the floods that occurred in March 2019. The annual and monthly variation and statistical characteristics of maximum daily rainfall variation were examined in the Karkheh River Basin, located in western Iran's Zagros Mountain. The return period of the extreme rainfall intensity is estimated by various probability distributions. The result shows maximum daily rainfall demonstrated an increasing trend. While the Gumbel distribution proved most effective for the long-term data at Khorramabad, the Inverse Gamma distribution provided the best fit for shorter data periods, estimating return periods of 50 to 200 years for extreme rainfall in others. However, at the Poldokhtar and Nurabad stations, which recorded maximum daily rainfall of 139.1 mm and 101 mm, respectively, in March and April 2019, the statistical distributions indicated return periods ranging from 70 to 200 years.

Keywords: Karkheh River Basin, Maximum daily rainfall, rainfall return period analysis, climate change Impact, Zagros Mountains.

1- Introduction

Precipitation is a fundamental atmospheric phenomenon characterized by significant spatial and temporal variability, influenced by various factors. Heavy precipitation events often trigger secondary hazards such as flash floods and landslides, which are becoming more frequent worldwide (Liu, 2024). Extreme precipitation events can lead to excessive surface runoff, resulting in floods that cause severe social and economic consequences. These events can lead to loss of human life, damage to infrastructure and agricultural products, and disruptions in transportation and essential services, ultimately impacting multiple economic sectors (Kheradmand et al., 2018; Ødemark et al., 2023). Extreme rainfall events have a large impact on society and can lead to loss of life and property, for example, by causing landslides or flooding due to dike breach or dam failures (Van De Vyver, 2012). Accurate management of water resources (e.g. irrigation, consumptive water supply) and effective agricultural activities depend on evaluating and understanding rainfall's characteristics (Tosunoglu & Gurbuz, 2019). Since damage from natural disasters has increased due to anomalous global climate changes,

researchers have become interested in studying their occurrences. The increasing frequency and intensity of extreme weather events, particularly heavy rainfall and floods, are a growing global concern. Climate change has been linked to the intensification of such extremes, including heavy precipitation events. According to the IPCC's 6th Assessment Report, if global warming is not limited to 1.5°C, the frequency and severity of these events are projected to rise (Zhou et al., 2024).

The analysis of rainfall data is quite crucial; hence it has always been a research area for hydrologists, meteorologists and decision-makers. The study of heavy rainfall is important in regional risk assessment. One of the primary steps is to determine the most appropriate probability distribution for the observed rainfall data. To quantify the risks associated with these disasters, reliable return period analysis is essential. Rainfall intensity patterns for various return periods are required for designing hydraulic structures or for flood mapping and zoning (Van De Vyver, 2012).Estimating precipitation intensity for different return periods is essential in many hydrological models and computational processes, including heavy rainfall forecasting. The intensity, duration, and frequency relationship varies for each precipitation event (Moradi & Ranjbar, 2019).

The return period of precipitation indicates how often a specific rainfall magnitude is likely to occur. In particular, the N-year return level is a key output of an extreme value analysis; hence, care needs to be taken to ensure that the model is accurate and that the level of imprecision in the parameter estimates is made explicit (Shaharudin et al., 2019). One of the key factors in return period analysis is the length of the statistical record. However, in the study area, data unavailability or the insufficiency of existing records often pose a challenge (Moradi & Ranjbar, 2019). However, the selection of an appropriate probability distribution is not an easy task since there are many possible distributions that could be used (Mamoon & Rahman, 2017). Many probability distributions exhibit similarities in their central regions but differ significantly in their tails. Therefore, multiple distributions can be fitted to precipitation data, leading to different estimations of return periods (Malehinezhad et al., 2015). Extreme value theory is the branch of probability and statistics dedicated to characterizing the behavior of extreme observations (Van De Vyver, 2012). Fitting distributions used to find a statistical distribution that best fits a data set are generated by random processes. A common problem that can be found in fitting distribution is to identify which distribution is suitable to a set of observations for a variable (Shaharudin et al., 2019). One does this to be able to simulate data based on the chosen distribution. It is important to identify the best fitting distribution because inappropriate distribution will affect the generated data and, onwards will certainly result in wrong decision (Amin et al., 2016; Mamman et al., 2017). Over the last decade, various researchers have intended to define the most suitable probability distribution for the rainfalls observed in different parts of the world. Dahamsheh and Aksoy (2007) found that three distinct regions are well identified by the log-Pearson type III, three-parameter log-normal and gamma distributions in Jordon. The Generalized Pareto was found to be the most appropriate distribution in describing the daily torrential rainfall amounts of Peninsular Malaysia (Shaharudin et al., 2019). According to the ranking-based scoring evaluation, the gamma, log-logistic, two-parameter log-normal, normal and Weibull distributions, which show the best fit for 78% of the data series, were mainly found to be the most suitable distributions in Turkey (Tosunoglu & Gurbuz, 2019). The gamma distribution is suitable for roughly 98% of the locations over all months in Africa (Husak et al., 2007). The generalized extreme value (GEV) distribution has been used in many studies and often provides a good fit to extreme rainfall maxima. It is well recognized that a satisfactory fit of the GEV distribution to a single record does not guarantee

good estimates of large return period events (Van De Vyver, 2012). Consistency of GEV distributions for various durations is obtained by fitting a smooth function to the preliminary estimations of the shape parameter in Belgium (Van De Vyver, 2012). The results showed that the inverse gamma statistical distribution compared to other distributions had the highest accuracy in determining in Ilam rainfall intensity (Moradi & Ranjbar, 2019). The results showed Generalized Pareto(GPA) at Abali and Mehrabad stations, Generalized logistic (GLOG) at Doshantapeh and Northern Tehran stations and 3-parameter log-normal (LN3) at Karaj station have a better fit to data (Malehinezhad et al., 2015). Vaheddoost and Aksoy (2017) used -probability distributions to model the annual rainfall data in Lake Urmia Basin, Iran, and they concluded that there is no particular distribution for all rainfall in the basin. Moreover, the west and southwest of the basin are well fitted by a normal distribution, while the northwest and middle parts of the basin are best characterized by a three-parameter log-normal distribution. P(year) showed that about 67% of the stations follow the Generalized Pareto (GP) distribution. Considering the P(max24h), 50% of the stations follow the GP distribution, and for the ratio of Pmax24h to Pyear, 50% of stations follow the Generalized Extreme Value (GEV) distribution in Semnan (Karami et al., 2023). In addition to precipitation amount, mountainous topography, soil characteristics, and land use play a crucial role in flood occurrence.

During March and April 2019, extensive flooding affected large parts of Iran, including Golestan Province (Rajabizadeh et al., 2019; Abdolalizadeh & Mohammadkhorshiddoust, 2023), Shiraz (Moradi & Ranjbar, 2019), and Khuzestan (Rajabizadeh et al., 2019; Seyghal et al., 2019; Peyravi et al., 2019; Fazel-Rastgar, 2020; Miri et al., 2023). The Karkheh basin is a flood-prone region in Iran that was severely affected by devastating river floods in 2019. A stark example of extreme weather impacts is the floods that struck Iran in March and April 2019, affecting one-third of the country's infrastructure and resulting in 76 fatalities (Sharifi & Bokaie, 2019; Shokri et al., 2020). Bayat-Afshary et al. (2022) concluded that the March and April 2019 flood was mainly intensified by rainfall intensity and snowmelt, whereas land-use changes during 2000–2018 were not considered major contributors. The floods in Khuzestan led to widespread inundation of cities and villages, disruption of road and rail transportation, and damage to agricultural lands. Additionally, significant losses were reported in industries, including the oil and energy sectors (Rajabizadeh et al., 2019). This event brought rainfall volumes equivalent to 150 times the aggregate flow of the region's major rivers, making the 2018-2019 rainy season the wettest in half a century (Dezfuli, 2020). This study aims to examine the temporal distribution of maximum daily and total rainfall in the Karkheh Basin. By analyzing the empirical statistical distribution and determining the best-fit mathematical distribution for daily maximum rainfall, the return period of extreme rainfall events will be assessed. This will provide insights to mitigate potential flood-related damages.

2- Study Area and Dataset

The study area is the Zagros Mountains, a major mountain range in western Iran that extends approximately 1,600 km from the northwest to the southeast of the country. This region plays a critical role in Iran's climate, acting as a barrier to atmospheric systems and influencing precipitation patterns. The Zagros Mountains are characterized by rugged terrain, high peaks, and deep valleys, with elevations exceeding 4,000 meters in some areas. The climate of the region varies from semi-

arid to Mediterranean, with precipitation largely concentrated during the winter and early spring months. The range is particularly susceptible to extreme weather events, including heavy rainfall, which often leads to flash floods and landslides. In March 2019, record-breaking floods caused extensive damage in the region. The unique topography of the Zagros Mountains, combined with its climatic conditions, makes it an ideal location for studying the return period of heavy rainfall disasters. Figure 1 presents a topographical map of the Karkheh Basin, located in western Iran, highlighting the distribution of total precipitation recorded during March and April 2019. The map illustrates the region's varied terrain, with the Zagros Mountains prominently influencing precipitation patterns. Areas of higher elevation, particularly in the western and northern parts of the basin, experienced significant rainfall, while lower-lying regions received comparatively less. This spatial variation in precipitation is crucial for understanding the hydrological dynamics of the basin, particularly to flood risk during extreme weather events like those observed in early 2019. The map effectively demonstrates how topography shapes rainfall distribution, providing insights into the localized impacts of atmospheric river phenomena.

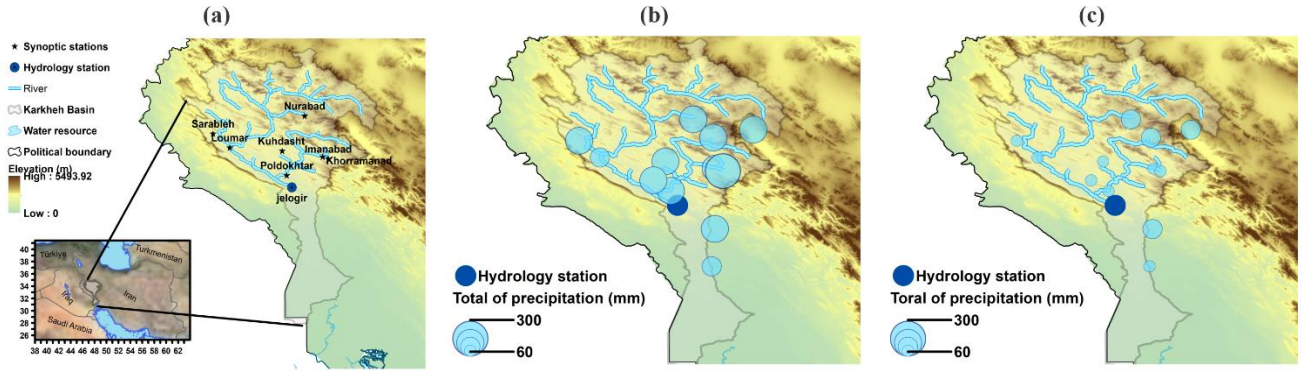


Figure 1: (a) Location, river, topography and synoptic station of Karkheh Basin in the western, total of precipitation (light blue circle) in Karkheh Basin during (b) March and (c) April 2019 and hydrological station position (dark blue circle).

Sentinel images on March 28, 2018 and March 28, 2019, are presented in Figure 2, illustrating the significant increase in water extent and the extensive flooding upstream of the Karkheh Reservoir.

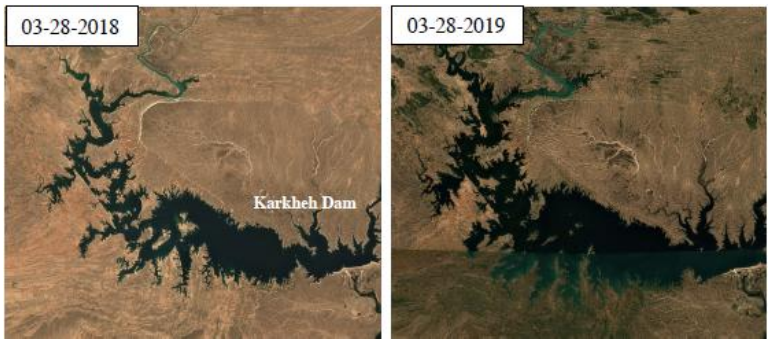


Figure 2 Spatial distribution of the March 28, 2018 , and March 28, 2019 flood event. Source: Fadaeifard and Danesh-Yazdi (2022)

Table 1 provides an overview of monitoring stations in the Karkheh Basin, detailing their geographical coordinates, elevation, data coverage period, and recorded precipitation during March and April 2019. Notably, the Poldokhtar station experienced the highest precipitation in March 2019, recording 139.4 mm, while Nurabad saw the highest rainfall in April 2019 with 101 mm. The data coverage varies significantly, with Khorramabad having the longest observation period of 72 years, and Imanabad the shortest with 14 years. This variation in data coverage highlights the challenges in analyzing long-term trends, particularly for stations with limited historical data.

Table 1. Monitoring stations in the Karkheh Basin, showing their geographical coordinates, elevation, data coverage period, and recorded precipitation (in mm) during March and April 2019

Station Name	Latitude	Longitude	Elevation (m)	Data Coverage (Years)	March2019 (mm)	April2019 (mm)
Khorramabad	33.43	48.28	1147.8	72	66	85.4
Kuhdasht	33.52	47.65	1197.8	25	63	21
Poldokhtar	33.15	47.72	713.5	24	139.4	17
Nurabad	34.05	48.00	1859	22	79.2	101
Sarableh	33.78	46.57	1045	16	41.7	38
Loumar	33.57	46.83	850	15	66	9
Imanabad	33.40	48.37	1500	14	117	31

2.1 Data Section

This study utilizes primary datasets, including historical precipitation records obtained from meteorological stations within the Karkheh Basin. These datasets provide crucial information on daily rainfall patterns, covering multiple decades of observations. The data includes key variables such as station location (latitude, longitude, and elevation) and precipitation measurements during significant rainfall events, particularly focusing on March and April 2019. The long-term data coverage from these stations enables robust statistical analyses for understanding the temporal distribution of rainfall and determining the return periods of extreme events.

2.2 Methodology:

Initially, data from seven available stations were analyzed using descriptive statistical methods, including mean, minimum, maximum, mode, median, standard deviation, skewness, and kurtosis. Given that some stations had limited data, only four stations with more than 20 years of records were selected for further analysis. The total annual and maximum 24-hour precipitation trends were examined over the available statistical period for each station. The Mann-Kendall method was used to determine these trends. Subsequently, the Probable Maximum Precipitation (PMP) was calculated using the Hershfield (1961), modified Hershfield, and Desa (2001) methods. The calculation methodology for the PMP is explained in the following sections.

- Probability Maximum Precipitation (PMP) analysis using the Hershfield method:

Hershfield is one of the founders of the statistical method of estimating 24-hour PMP applied when only precipitation records available. This estimate requires a series of 24-hour annual rainfall data at observation points (Hershfield, 1961, 1965). The Hershfield method is based on the PMP estimation based on the Chow equation (Chow, 1951) in rainfall frequency analysis (Willardson, 2011). In the Hershfield (1965) statistical method, the mean and standard deviation of the annual series of maximum rainfall data in temporal intervals (time duration) is calculated, and the statistical PMP value is obtained using the Equation (1).

$$X_{PMP} = X_n + S_n \times K \quad (1)$$

Where X_{PMP} is the Probable maximum precipitation in a given duration for a station, X_n is the mean of n observed annual maximum 24-h rainfall, S_n is the standard deviation of the series. The K is the frequency factor that depends on the availability of data period in every station, as well as in rainy and arid conditions, and rain durations of 24 h reported by Wmo (1986). The estimation of the frequency factor K plays a key role in the proper estimation of PMP. A very high value of K will lead to the over-estimation of PMP, and a lower value of K will lead to the underestimation of PMP, and therefore, any structure designed based on that PMP estimate will be exposed to higher risk. Hershfield (1965) found K to vary within a range from less than 3 to a maximum value of 15 extracted from 2700 stations in the United States. He found that K cannot have a universal value. So, he developed an empirical diagram on the mean X_n , K and rainfall duration. The value of K in this graph varies from 5 to 20. In 2001, Desa *et al.* In Malaysia, they introduced a different approach to the Hershfield method, in which only the highest observed criterion was applied, leading to a sharp decrease in the frequency coefficient (Desa M et al., 2001; Desa M & Rakhecha, 2007). In this method, the K_m coefficient is obtained using Equation (2).

$$K_m = \frac{X_{max} - X_{n-1}}{S_{n-1}} \quad (2)$$

X_{max} is the highest rainfall value at the station, X_{n-1} is the mean of the annual extreme series without the largest value, and S_{n-1} is the standard deviation of the annual extreme series without the largest value. X_{PMP} which is the highest rainfall value at the station calculated by Equation (3), maximum K_m selected for all stations.

$$X_{PMP} = X_n + S_n \times K_m \quad (3)$$

In the present study, the Hershfield method with a K_m factor of 15 was employed as the first approach. In the second method, a K_m factor of 6 was considered based on the study by Fattahi and Habibi (2022), and the adjusted Desa M and Rakhecha (2007) method was used as the third approach for estimating the Probable Maximum Precipitation (PMP). In the Desa M and Rakhecha (2007) method, the mean and standard deviation were calculated after excluding the recorded maximum precipitation. Subsequently, the K_m factor for each station was determined using Equation 2. The highest K_m value obtained among the stations was selected, and then the PMP for all four stations was calculated using Equation 3.

It should be noted that, although according to Desa et al. (2001), a long data series is required for PMP estimation, due to limitations in observational data, PMP was calculated for the study area using different methods for the four stations with the longest available historical records. The results are presented in subsequent sections. Furthermore, the empirical

return period and several mathematical return period methods were examined for the available statistical period for each of the four stations. A detailed explanation of the return period is provided in the following sections.

- *Return period*: Statistical distribution of extreme rainfall events:

In this study, we selected daily (24-hour) maximum precipitation to capture the characteristic patterns of extreme rainfall events. Additionally, we analyzed indicators such as the annual maximum daily precipitation to further understand the extremes. Choosing the best-fit probability distribution model for each location is critical for accurate analysis. In this section, we present the commonly used probability distribution models for extreme rainfall analysis. The methods of parameter estimation, goodness-of-fit tests (both numerical and graphical), and the procedure for estimating return periods are also discussed. This section outlines the methodology employed to analyze the return periods of heavy rainfall events in the Zagros Mountains.

The HyfranPlus software was used to evaluate different probability distributions of daily maximum precipitation and to calculate the return periods.

- Empirical probability

The empirical method is nonparametric. The empirical probability formula is given by:

$$f(x) = \frac{k-a}{n-2a+1} \quad 0 \le a \le 0.5 \qquad (4)$$

where k represents the rank and n denotes the total number of data points. The parameter a varies across different distributions. For the Weibull distribution, $a = 0$, and the formula is modified as follows:

$$\mathrm{f}(x) = \frac{k}{n} \qquad (5)$$

$$T = \frac{1}{1-f(x)} \quad q = f(x)\ for\ non\ excedence\ probalitiyt\ \ T = \frac{1}{1-q}\ or\ T = \frac{1}{p} \qquad (6)$$

The empirical distribution was employed to examine the conditions of daily maximum precipitation and the return periods of actual data from the selected stations. The return period is derived from the inverse of the probability of occurrence.

- Probability distributions of applicants (*PD*)

By utilizing these distributions, we can rigorously analyze rainfall extremes in our study area, estimate return periods, and assess the risk of future heavy rainfall events. Most probability distributions have been proposed for on-site analyses of rainfall, wind, and temperature (Fawad et al., 2018). Each distribution possesses unique characteristics that render it suitable for different types of data and analyses. In this study, maximum daily rainfall data were analyzed using several distributions, including the generalized extreme value (GEV), log-Normal, Pearson type-III (P3), Gumbel (GUM), and Inverse Gamma distributions.

- Generalized Extreme Value distribution (GEVD): The generalized extreme value (GEV) method is a parametric approach that combines three types of extreme value distributions—namely, the Gumbel, Fréchet, and Weibull distributions—into a single formula. The GEV distribution requires three parameters: location, scale, and shape (Coles, 2001). Rare precipitation events can be effectively characterized by analyzing the behavior of the upper tail of the GEV distribution function. The GEV distribution is fitted to "block" maxima (in this case, the annual maxima) and inverted to provide estimates of long return periods across a range of sample sizes and return intervals.

- Log-Normal: The log-normal distribution is a continuous probability distribution in which the logarithm of the variable is normally distributed. It is commonly employed to model non-negative data with right-skewed distributions, such as rainfall amounts. This makes it particularly useful for modeling extreme rainfall events, as it provides a more accurate representation of the distribution of daily precipitation totals. By fitting the log-normal distribution to the rainfall data, we can derive important statistical parameters, such as the mean and variance, which are critical for risk assessment and management in hydrology. Additionally, the log-normal model can facilitate the estimation of return periods for extreme rainfall events, aiding in the planning and implementation of effective flood mitigation strategies.
- Log-Normal3: The three-parameter lognormal distribution is a general skew distribution used in hydrologic analysis of extreme floods, seasonal flow volumes, duration curves for daily streamflow, rainfall intensity-duration, soil water retention, etc. A procedure for its application has been suggested using only the median, the mean, and the standard deviation of the original data.
- Pearson Type III: One of the most commonly used distributions in hydrology is the P3 distribution, which is a two-parameter Gamma distribution with a third parameter for the location. The Pearson Type III distribution is a flexible parametric model frequently utilized in hydrological studies for flood and extreme rainfall frequency analysis. This distribution is characterized by its ability to accommodate skewed data, making it particularly suitable for modeling non-negative variables such as flood magnitudes and daily rainfall totals. The probability density function (PDF) of the Pearson Type III distribution is defined in terms of its mean, standard deviation, and skewness, allowing for a comprehensive representation of the underlying data characteristics. Its adaptability to varying levels of skewness makes it a valuable tool for hydrologists seeking to analyze and predict extreme events. By fitting the Pearson Type III distribution to historical precipitation or flood data, researchers can estimate critical parameters such as return periods and exceedance probabilities. This information is essential for flood risk management, infrastructure design, and water resource planning, as it helps stakeholders make informed decisions based on the likelihood of extreme hydrological events occurring in the future. The frequency factor k is obtained from the theoretical table available for the Pearson type III distribution with the skew coefficient (Patra, 2001).

- Gumble: The extreme value type I distribution, commonly referred to as the Gumbel distribution, is frequently employed to represent maximum processes, such as maximum rainfall, flood discharge, or minimum streamflow and pollutant concentration. This distribution is particularly useful in analyzing the distribution of extreme events because it effectively models the tails of the distribution, which are crucial for understanding the behavior of rare occurrences. The Gumbel distribution has been widely adopted in various countries, including Finland and Spain, where it has been identified as the best-fit distribution for flood data (Fawad et al., 2018). By fitting the Gumbel distribution to extreme value data, researchers can derive critical statistical parameters, including the mean and variance, which are essential for estimating return periods and assessing the risks associated with extreme hydrological events. Additionally, the Gumbel distribution provides valuable insights into the probability of occurrence for specific thresholds of interest, facilitating better flood risk management and informing infrastructure design. Its application extends beyond hydrology, making it a versatile tool in various fields, such as meteorology and environmental science, where understanding extreme behavior is vital for effective planning and response strategies.
- Inverse Gamma: In probability and statistics, the inverse gamma distribution is a two-parameter family of continuous distributions on the positive real line, which is the distribution of the reciprocal of a variable distributed according to the gamma distribution. The Inverse Gamma distribution belongs to the exponential family and has positive support. Applied in reliability studies for modeling time-to-failure distributions. Often used as a conjugate prior in Bayesian inference for variance-related parameters. It can handle a wide range of variance levels, from small to large. Simplifies Bayesian updates when coupled with Gaussian probabilities, making computational inference more efficient. Inverse gamma parameters have clear meanings, such as scale and shape, which are useful in physical interpretation.

Table 2 outlines the respective probability density functions (PDFs) and their associated parameters, including the shape parameter, scale parameter (Variance), and position parameter (Mean). Understanding these distributions and their parameters is crucial for accurately modeling and analyzing extreme rainfall events and other natural phenomena, as they provide insights into the behavior and risks associated with rare occurrences. The selection of an appropriate marginal distribution is essential for reliable statistical inference and risk assessment in various fields, including hydrology, meteorology, and environmental science.

Table 2. Six marginal distribution functions

Marginal distribution type	Probability Density Function (PDF)	Parameters
Generalised Extreme Value (GEV)	$f(x) = \frac{1}{\alpha}\left(1 - k\frac{x-u}{\alpha}\right)^{\frac{1}{k}-1} \exp\left\{-[1 - \frac{k}{\alpha}(x-u)]^{\frac{1}{k}}\right\}$	k is the shape parameter u is the position parameter α is the scale parameter $\left(1 + k\frac{x-u}{\sigma}\right) > 0$
Log-Normal	$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left\{-\frac{[lnx - \mu]^2}{2\sigma^2}\right\}$	μ is the position parameter σ is the scale parameter
Log-Normal3	$f(x) = \frac{1}{(x-m)\sigma\sqrt{2\pi}} \exp\left\{-\frac{[ln(x-m) - \mu]^2}{2\sigma^2}\right\}$	σ is the shape parameter μ is the position parameter

Gumbel	$f(x) = \left(\frac{1}{\alpha}\right) exp\left[-\left(\frac{x-u}{\alpha}\right) - exp\left(-\left(\frac{x-u}{a}\right)\right)\right]$	m is the scale parameter u is the position parameter α is the scale parameter
Pearson Type III	$f(x) = \frac{\alpha^{\lambda}}{\Gamma(\lambda)} (\mathrm{x} - \mathrm{m})^{\lambda-1} \exp - [\alpha(x-m)]$	λ is the shape parameter α is the scale parameter
Inverse Gamma	$f(x) = \frac{\alpha^{\lambda}}{\Gamma(\lambda)} (\frac{1}{x})^{\lambda+1} \exp(-\alpha/x)$	λ is the shape parameter α is the scale parameter

- **Estimation parameters of PDs by the maximum likelihood**

The GPD parameters were estimated using the maximum likelihood method in this study. However, the MLE and L-moments are widely used in part due to the widespread availability of easy-to-use software (Hosking & Wallis, 1997; Gilleland & Katz, 2016). In this paper, we consider the two most commonly used approaches of (MLE) maximum likelihood estimation (Coles et al., 2001). We have also applied maximum likelihood estimation (MLE)

- The goodness of fit tests

The specific probability distribution (PD) chosen for analysis depends on several factors, including the comparison of different distributions, the availability of maximum rainfall data, and the method of parameter estimation. In the current study, we applied the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to assess the variability and performance of the different distribution models. These criteria provide a quantitative basis for model comparison, helping to identify the distribution that best fits the observed maximum rainfall data. The advantages of both graphical and statistical tests for goodness of fit have been demonstrated in various studies involving maximum rainfall data (Yuan et al., 2018; Wang & Anwar, 2021). In the context of climate change, employing goodness-of-fit tests is crucial for selecting the most appropriate distribution model for accurate rainfall predictions. Accurate goodness-of-fit assessments not only enhance the reliability of the selected distribution but also improve our understanding of extreme rainfall behavior under changing climate conditions. By identifying the best-fit distribution, we can obtain more precise estimates of return periods and associated risks, which are essential for effective flood risk management and planning. Moreover, as climate change continues to alter precipitation patterns, the robustness of our statistical models becomes increasingly important. Utilizing goodness-of-fit tests in conjunction with L-moments and other statistical methods allows us to adapt to these changes and develop strategies that mitigate the potential impacts of extreme rainfall events on infrastructure and ecosystems. This holistic approach fosters resilience and supports informed decision-making in the face of climate uncertainty.

3- Results and Discussion

3.1 Long-term maximum daily precipitation

The daily maximum rainfall of selected stations in the Karkheh Basin was statistically analyzed. Figure 3 illustrates two key statistical visualizations of maximum daily precipitation across stations in the Karkheh Basin: (a) a box plot showing the distribution of maximum daily precipitation values and (b) a density plot depicting the distribution of these values. The box plot (a) highlights the variability and spread of precipitation at each station, with stations like Poldokhtar and Nurabad exhibiting larger ranges and higher outliers, indicating more extreme rainfall events. The longest period of record belongs to Khorramabad, with 72 years of data, while the shortest is from Imanabad, with 15 years of data. The highest recorded rainfall was 139.4 mm at Poldokhtar and 117 mm at Imanabad. The lowest average daily rainfall was observed at Nurabad, while the highest was recorded at Imanabad. The greatest data variability was seen at Poldokhtar, Loumar, and Sarableh (see Figure 3 and Table 3). In Imanabad, the most frequent rainfall was 54 mm, while in Poldokhtar, it was 50 mm. The distribution plot (Figure 3b) provides a detailed view of how the maximum daily precipitation is distributed, revealing skewed distributions at several stations, suggesting that extreme precipitation events are not normally distributed across the basin. The distribution density of the data indicates that the daily maximum rainfall at none of the selected stations follows a normal distribution. At the Sarableh, Nurabad, and Imanabad stations, a bimodal distribution is observed, where the distribution trend decreases up to 80 mm of rainfall but then shows an increase beyond that value. Statistical indicators reveal that the distribution of daily maximum rainfall is not normal at any of the stations. All stations exhibited positive skewness, indicating a tendency of the data toward extreme values. Kuhdasht and Loumar had the least skewness and negative kurtosis, suggesting a more symmetrical distribution compared to the other stations. The highest skewness of 1.73 and kurtosis of 3.15 were recorded at Nurabad and Imanabad, respectively. These visualizations offer critical insights into the rainfall patterns and the occurrence of extreme weather events in the region. Further analysis will be conducted for the four stations of Khorramabad, Kuhdasht, Poldokhtar, and Nurabad, each with a statistical period exceeding 20 years. Although significant rainfall amounts were recorded in March and April 2019 at three other stations, the short duration of the available data renders any further analysis—particularly the estimation of return periods—prone to errors. Therefore, this discussion will refrain from providing additional details regarding these three stations.

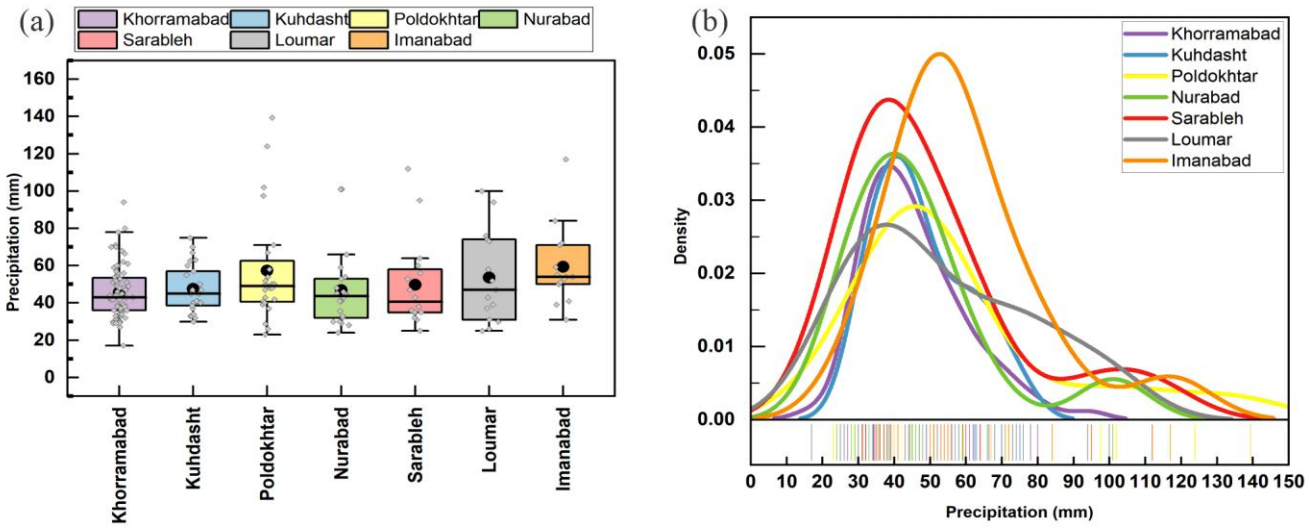


Figure 3 : (a) Box plot of Maximum daily precipitation, (b) distribution of Maximum daily precipitation, in Karkheh stations

Table 3 provides a statistical summary of annual maximum precipitation data for seven stations in the Karkheh Basin. The data highlights significant variability in both mean and maximum precipitation across the stations. Poldokhtar recorded the highest maximum precipitation of 139.4 mm, while Imanabad had the highest mean of 59.4 mm. Skewness and kurtosis values indicate varying degrees of asymmetry and peakedness in the data, with Nurabad and Imanabad exhibiting the highest skewness and kurtosis, suggesting a heavier tail and more extreme events. In contrast, Kuhdasht and Loumar show negative kurtosis, indicating more flattened distributions. These variations emphasize the diverse rainfall patterns across the region.

Table 3. Statistical Summary including mean, minimum, maximum, mode, median, standard deviation, skewness and kurtosis of Maximum daily Precipitation (mm) Data

	N(years)	Mean	Minimum	Maximum	Mode	Median	Standard Deviation	Coefficient of Variation(%)	Skewness	Kurtosis
Khorramabad	72	45.6	17	94	36	43	14.2	31.14	0.97	1.12
Kuhdasht	25	47.6	30	75	33	45	12.9	27.10	0.60	-0.65
Poldokhtar	24	57.4	23	139.4	50	49	29.7	51.74	1.58	2.02
Nurabad	22	46.8	24	101	30	43.7	20.5	43.80	1.73	2.99
Sarableh	16	49.8	25	112	35	40.5	24.0	48.19	1.64	2.35
Loumar	15	53.7	25	100	--	47	24.5	45.62	0.63	-0.77
Imanabad	14	59.4	31	117	54	54	21.6	36.36	1.52	3.15

The trend analysis was performed for all four stations using the Mann-Kendall method. The total annual precipitation at all four stations during the statistical period does not show significant trends, indicating that the annual rainfall amounts have not exhibited a consistent increase or decrease over the years analyzed Figure 4. The obtained *P-values* for Khorramabad, Kuhdasht, Poldokhtar, and Nurabad were 0.038, 0.26, 0.009, and 0.88, respectively. This indicates that an increasing trend in maximum daily precipitation is confirmed for Poldokhtar, while a gradual trend is observed in Khorramabad. An increasing trend in daily maximum precipitation in the Karkheh Basin has also been documented in previous studies (Dana et al., 2021). However, no significant trend changes are evident in Kuhdasht and Nurabad.

Thus, by comparing the trends of total annual precipitation and daily maximum rainfall, it can be concluded that although the overall rainfall amounts do not exhibit a clear trend, the daily maximum rainfall is on the rise. Stations located on the western slopes of the Zagros Mountains experience heavier daily rainfall. The increase in the frequency and intensity of extreme daily rainfall events creates conditions conducive to flooding. This situation is particularly evident in the two stations of Nurabad and Poldokhtar, which experienced heavy rainfall in March and April 2019. In Kuhdasht, no significant trends were observed in total annual precipitation or daily maximum rainfall. Table 3 presents time-series plots that compare precipitation levels during March 2019 with historical data across multiple stations in the Karkheh Basin. These plots highlight the anomalous nature of the March 2019 rainfall, where several stations recorded significantly higher precipitation compared to long-term averages. The graphs show distinct peaks in precipitation, particularly at Poldokhtar and Nurabad, where rainfall levels far exceeded historical trends. This stark deviation underscores the extreme nature of the March 2019 atmospheric river event and its potential impact on flood risks in the region. The comparison with historical data helps contextualize the severity of the event.

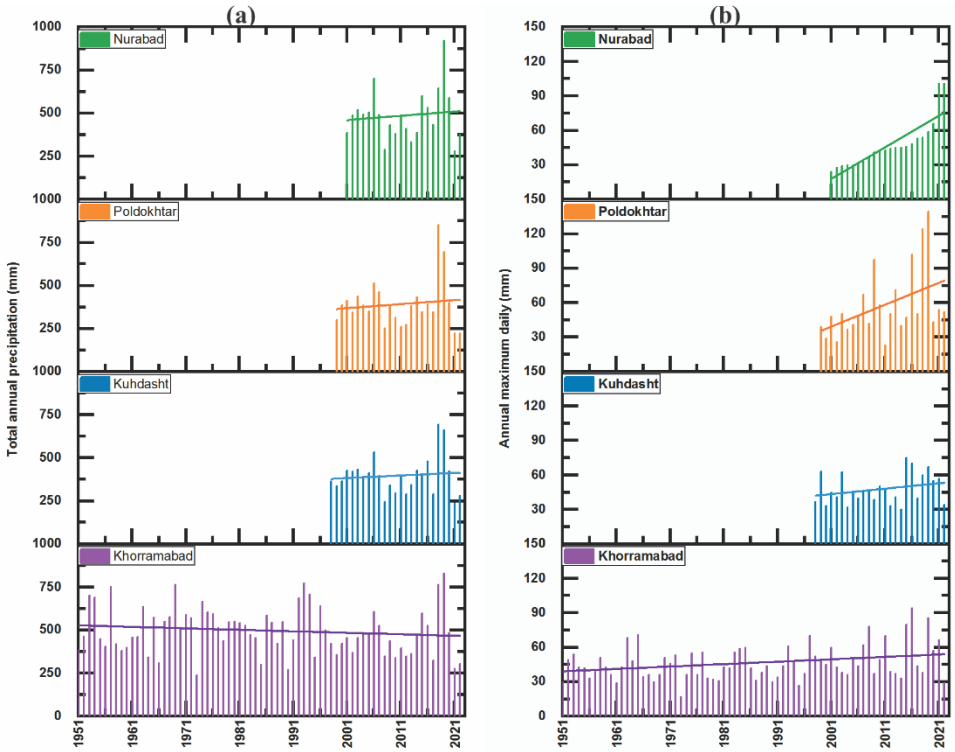


Figure 4: Time-series plots in Khorramabad, Kuhdasht, Poldokhtar and Nurabad. left panel: Total of Annual Precipitation (mm), right panel: Maximum daily precipitation (mm)

The highest 24-hour rainfall for each year in the study period was extracted for four selected stations. Using the percentile method, rainfall amounts were classified into three categories: values below the 25th percentile were defined as low rainfall, those between the 25th and 75th percentiles as normal rainfall, and values above the 75th percentile as heavy rainfall. Table 4 summarizes the rainfall thresholds associated with each category. At the four stations, the 0–25% (low rainfall) range spans 17 to 33 mm, with Kohdasht recording the highest threshold and Khorramabad the lowest. The normal (25–75%) rainfall range extends from 29.1 to 57 mm, with Kuhdasht and Poldokhtar exhibiting the upper bounds of this category. Rainfall amounts in the heavy (75–100%) category ranges from 52.1 to 139 mm, with Poldokhtar showing the highest value. Overall, Poldokhtar recorded the maximum 24-hour rainfall in the dataset, reaching 139 mm in March 2019.

Table 4 Range of maximum daily precipitation for various categories using the percentile approach

Precipitation	Percent(%)	Khorramabad	Kuhdasht	Poldokhtar	Nurabad
Low	0-25	17-31	30-33	23-31	24-29
Normal	25-75	31.1-54	33.1-57	31.1-60	29.1-52
Heavy	75-100	54.1-94	57.1-75	60.1-139	52.1-101

Figure 4 illustrates the differences between the minimum and maximum daily rainfall amounts within each percentile-based group. The largest variability in the low-rainfall category occurs at Khorramabad Station, with a range of 14 mm. In the normal-rainfall category, Poldokhtar exhibits the greatest spread at 29 mm. The heavy-rainfall category shows the largest overall variability, with a range of 49 mm, again centered at Poldokhtar. These results indicate that Poldokhtar experiences greater fluctuations in daily rainfall compared with the other stations, particularly in the normal and heavy rainfall groups. The extreme 24-hour rainfall of 139 mm in March 2019 notably contributes to the high variability observed in the heavy-rainfall category. A similar, though less pronounced, pattern is also evident within the normal-rainfall range. Hasanvand et al. (2023) concluded that an average precipitation of 47 mm in the Karkheh basin can be considered heavy rainfall, and that the basin is highly susceptible to flooding from such intense precipitation. In other words, heavy rainfall in this basin quickly leads to flood events.

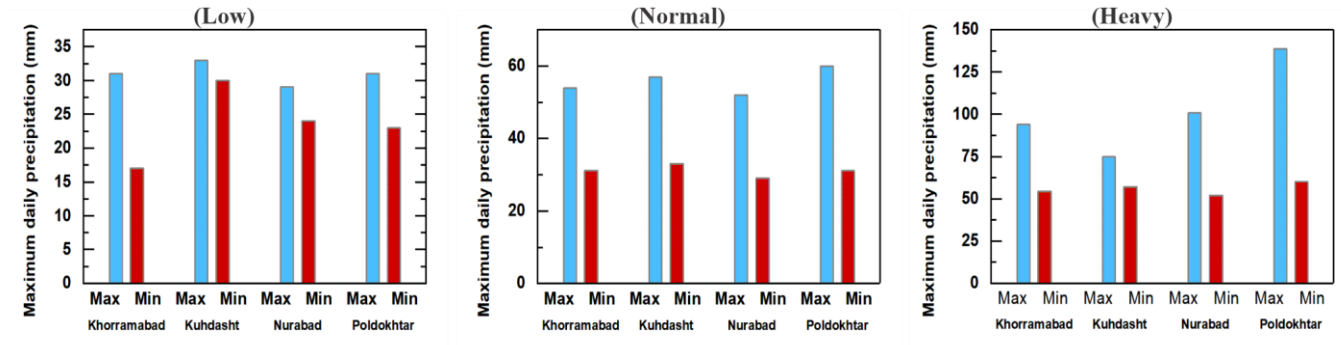


Figure 5. Maximum and minimum 24-hour precipitation values across four stations (Khorramabad, Kuhdasht, Nurabad, and Poldokhtar) for the three percentile-based rainfall categories: Low (<25th percentile), Normal (25th–75th percentile), and Heavy (>75th percentile). The bars illustrate the range of variability within each category.

The distribution of low, normal, and heavy rainfall across the four selected stations was also analyzed (Table 5). At all stations, the largest proportion of events falls within the 25th–75th percentile range, corresponding to normal rainfall. However, it is notable that at every station, the proportion of heavy rainfall events (75th–100th percentile) exceeds that of low rainfall events. Specifically, heavy rainfall accounts for 25% of events at Khorramabad, 28% at Kuhdasht, 25% at Poldokhtar, and 27% at Nurabad. This pattern indicates that the region experiences a substantial frequency of intense daily rainfall events.

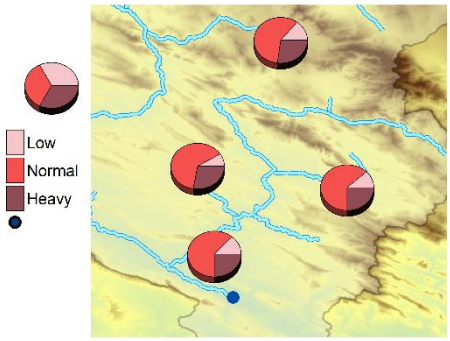


Figure 6 Percentage of maximum daily precipitation by low, normal, and Heavy Categories

The 99th-percentile threshold represents very heavy or extreme 24-hour precipitation. At this percentile, the rainfall amounts are 66 mm for Khorramabad, 63 mm for Kuhdasht, 98 mm for Poldokhtar, and 71 mm for Nurabad. For each station, precipitation events were evaluated against the 99th percentile threshold, and the dates of events equal to or exceeding this threshold were extracted (Table 5). Four major heavy rainfall events in the Karkheh Basin, with corresponding discharge measurements at the Jelogir hydrometric station, were analyzed (Table 5 and Figure 7). In November 2018, Poldokhtar recorded 102 mm of precipitation, and in February 2020, Nuurabad recorded 101 mm, both corresponding to the 99th percentile of their precipitation. At the other three stations, precipitation remained below the 99th percentile. The reported runoff for these events was 1,604 m^3/s in November 2018 and 2,748 m^3/s in February 2020. Both events occurred during the cold season (autumn and winter). In April 2016, three stations, Khorramabad, Kuhdasht, and Poldokhtar, exceeded their extreme thresholds. The reported discharge in April 2016 was 1,689 m^3/s. The April 2016 flood has been examined in previous studies from various perspectives (Dizaji et al., 2019; Shirali, 2020; Akhavan Gouran et al., 2022; Khoshakhlagh et al., 2023). Three people were killed during the April 2016 floods, with Ilam, Lorestan, and Khuzestan being the most severely affected provinces (Reliefweb, 2016).

However, conditions from March 25 to April 1, 2019, were different. On March 25, 2019, all four stations recorded extreme precipitation, and the discharge reached 1,359 m^3/s, flooding occurred in the region. The most remarkable case is the 139.4 mm of rainfall within 24 hours at Poldokhtar, the station located upstream and closest to the hydrometric gauges. A few days later, a second weather system affected the area, producing additional rainfall; however, on March 31 and April 1, not all four selected stations recorded extreme precipitation. Despite this, the discharge increased up to 4,688 m^3/s, causing extensive damage across several provinces. Bayat-Afshary et al. (2022) reported that the discharge recorded at the

Jelogir station upstream of Karkheh Dam during the 2019 event corresponded to an exceptionally rare 262-year return period, exceeding the magnitude of all historical floods in the region. On March 31 and April 1, 2019, Nurabad recorded extreme precipitation values of 70 mm and 101 mm, respectively, while the other stations recorded lower precipitation amounts.

Table 5 The events with the highest daily precipitation (mm) in 99% of the data are called very extreme in the Karkheh basin

Date	Khorramabad mm (percent)	Kuhdasht mm (percent)	Poldokhtar mm (percent)	Nurabad mm (percent)	Runoff (m^3/s)
14,15/4/2016	94 (99%)	70 (99%)	102 (99%)	66	1689
25/11/2018	38	21	124 (99%)	34	1604
25/03/2019	66 (99%)	63 (99%)	139.4 (99%)	79.2 (99%)	1359
31/03/2019	52	55	55.6	70 (99%)	679
01/04/2019	85.4(99%)	21	0	101(99%)	4688
6,7/02/2020	57	55	25	101 (99%)	2748

In two cases, November 2018 and February 2020, both occurring during autumn and winter, river discharge responded rapidly to three consecutive days of rainfall. In these events, discharge increased during the precipitation period and decreased immediately upon rainfall cessation, reflecting a typical rainfall-runoff relationship (Figure 7 b and c). Considering that previous studies have reported the average annual discharge of the Karkheh River to range between 20 and 332 m^3/s (Dana et al., 2021), these values represent significant increases. However, because these events occurred in the cold season and the discharge fell quickly after rainfall cessation, the resulting floods did not cause severe damage to the surrounding areas. Rainfall amounts during these events were 124 mm at Poldokhtar in November 2018 and 101 mm at Nurabad in February 2020. In contrast, the events of April 2016 and March 2019 exhibited markedly different hydrological behavior. The relationship between rainfall and runoff during the March 2019 and April 2016 events will be analyzed. It is also noteworthy that both systems occurred in spring, consistent with previous research indicating that most major floods in the Karkheh Basin occur during this season (Dana et al., 2021). In April 2016, precipitation continued for five consecutive days, and the total rainfall across the four stations exceeded that of the previous two events. The discharge also reached maximum values for two consecutive days. This event produced flooding primarily in adjacent basins rather than at the Jelogir station (Shirali, 2020), suggesting either (1) prior rainfall had already saturated the basin and raised discharge levels, or (2) heavier rainfall occurred at stations outside the Jelogir upstream area.

The March 2019 event was even more extreme. Several rainfall episodes occurred throughout the month, with the most intense rainfall falling between 23 March to 1 April (Figure 7c). Although the second precipitation event had lower rainfall amounts than the first, the runoff volume increased substantially. The first rainfall, maintaining elevated soil moisture and basin wetness. Furthermore, water releases from the Karkheh Dam during this period—due to repeated rain events—likely contributed to downstream discharge levels. According to the Fadaeifard and Danesh-Yazdi (2022), the presence and

management of dams in 2019 and 2020 contributed effectively to flood mitigation, especially during the severe flood events of those years.

Although the discharge decreased afterward, it remained considerably above normal. The rainfall on 23–24 March triggered a severe and destructive flood across the Karkheh Basin, particularly in the Poldokhtar region, where extensive damage occurred. Additional rainfall at the end of March caused another discharge increase, followed by a gradual decline as rainfall intensity decreased. According to the Dezfuli (2020), the atmospheric river crossing the Zagros Mountains generated record orographically-induced rainfall, leading to severe flooding, extensive infrastructure damage, and at least 76 fatalities in Iran in March-April 2019.

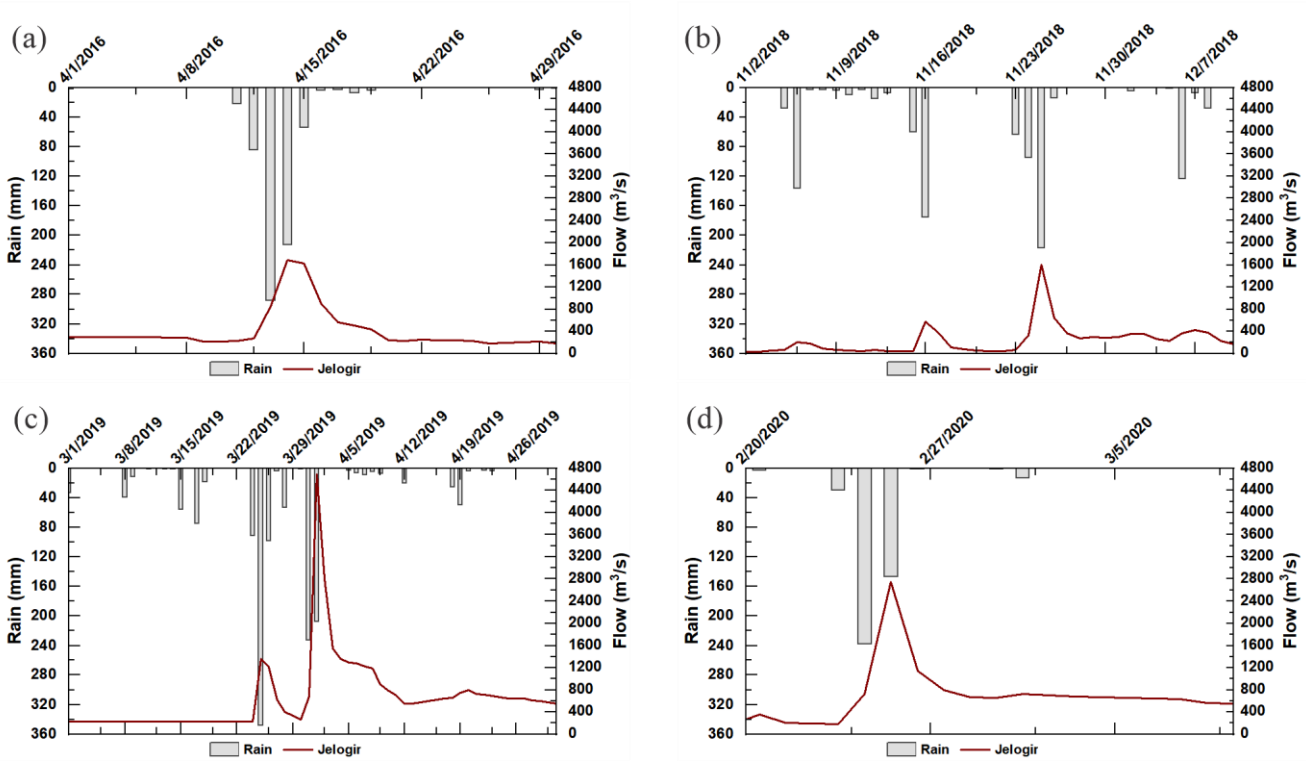


Figure 7 The hyetograph of total daily precipitation in selected stations and runoff in Jelogir hydrology station in Karkheh basin.

Because the March 2019 flood caused severe regional impacts and extensive damage, and given its exceptional magnitude, the long-term monthly precipitation distribution at the four selected stations was analyzed and compared with the precipitation recorded in March 2019. Figure 8 displays the monthly maximum daily precipitation (24-hour totals) recorded at the selected stations in the Karkheh Basin throughout the study period. The figure illustrates significant variability in precipitation patterns across the stations, with distinct peaks indicating extreme rainfall events during specific months (Figure 8). Notably, some stations, such as Poldokhtar and Nurabad, exhibit higher maximum daily precipitation values compared to others, suggesting localized weather phenomena or geographical influences affecting rainfall distribution. The monthly distribution of daily maximum rainfall in 2019, compared to the long-term statistical period at

the Khorramabad station, indicates that the rainfall events occurring in March and April 2019 were lower than the daily maximum rainfall recorded at this station over the long term (Figure 8). Therefore, the rainfall experienced in Khorramabad in 2019 does not qualify as extreme relative to the entire statistical period. In contrast, at three other stations, the rainfall recorded in March 2019 exceeded the daily maximum rainfall for March across the entire period. This difference is particularly notable at Poldokhtar. The trends captured in this figure highlight the importance of understanding regional precipitation extremes, which are critical for assessing flood risks and informing water resource management strategies. At Nurabad, the rainfall in March and April 2019 surpassed that of the long-term statistical period for the station. The increase in rainfall, especially in March 2019, at the upstream stations of Nurabad and Poldokhtar, was a significant factor contributing to the rise in river discharge and the occurrence of flooding in the Karkheh Basin.

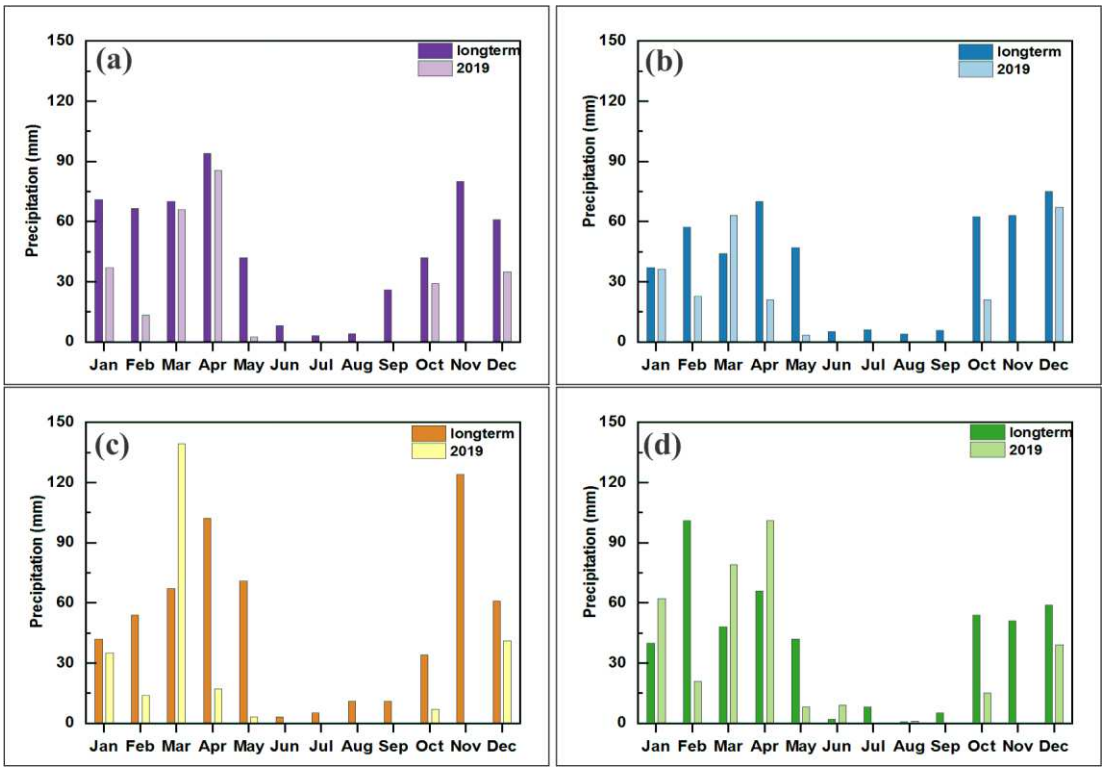


Figure 8: Comparing precipitation Monthly maximum daily precipitation (24-hour totals) recorded for historical data and March 2019 at (a) Khorramabad, (b)Kuhdasht, (c) Poldokhtar and (d) Nurabad stations over the study period

4- Probability Maximum Precipitation (PMP)

Although significant trend changes in maximum daily precipitation should not exist for PMP calculation, due to the limited number of stations, the short data record for three stations, and the absence of trend changes in two stations, PMP was calculated for all four stations. Using the Hershfield (1961) method with a K_m factor of 15, the estimated PMP values were notably high, reaching 502.8 mm for Poldokhtar. In contrast, when using the modified Hershfield method with a K_m factor of 6, the PMP values decreased significantly, reducing the estimate for Poldokhtar to 235.58 mm. In the third

approach, K_m values for each station were calculated by excluding the maximum precipitation. These values were similar for Khorramabad (3.50), Nurabad (3.48), and Poldokhtar (3.34). Kuhdasht exhibited the lowest K_m value of 2.43. Due to the limited number of stations, plotting K_m values against mean precipitation was not feasible. However, considering the close K_m values among the three stations and previous studies, the highest value of 3.50 from Khorramabad was used to estimate PMP. Using the Desa method, the PMP values were determined as 161 mm for Poldokhtar, 118.8 mm for Nurabad, 98.3 mm for Khorramabad, and 92.6 mm for Kuhdasht. The ratio of the PMP (Desa M et al., 2001) to maximum daily precipitation was calculated, with the highest ratio of 1.18 observed at Nurabad and the lowest ratio of 1.05 at Khorramabad. This indicates that daily precipitation events of up to 118.8 mm are plausible for Nurabad. Similarly, for Poldokhtar, a 24-hour precipitation of 161 mm is possible, representing a 1.16-fold increase over the observed maximum of 139.4 mm. A comparison of Table 4 and Table 6 revealed the maximum probable precipitation estimated using the Desa (2001) method is closer to the recorded maximum daily rainfall in heavy rain events. In Poldokhtar, where the maximum recorded rainfall is 139 mm, there is a likelihood of 161 mm of precipitation occurring probability.

Table 6: PMP (mm) calculation with Hershfiled, Modeified Hershfiled and Desa (2001) method in Khorramabad, Kuhdasht, Poldkhtar and Nurabad

PMP method	**Stations (Years)**			
	Khorramabad (72)	**Kuhdasht (25)**	**Poldokhtar (24)**	**Nurabad (22)**
Hershfile ($K_m = 15$)	*268.8*	*240.4*	*502.8*	*355.0*
PMP (24)/P24	2.86	3.21	3.61	3.52
Modified (K_m=6)	*135.40*	*124.71*	*235.58*	*170.08*
PMP (24)/P24	1.44	1.66	1.69	1.68
Desa et al (2001)	*98.3*	*92.6*	*161.0*	*118.8*
K_m	3.50	2.43	3.34	3.48
PMP (24)/P24	1.05	1.23	1.16	1.18

4.1 Return Period

The fitting of return periods for statistical distributions and the empirical Weibull distribution was compared against the maximum daily rainfall (Figure 9). In the Khorramabad and Kuhdasht stations, the empirical distribution aligns well with the statistical distribution, particularly in Khorramabad, where the empirical return period for a maximum rainfall of 85 mm is 54 years, while the mathematical distributions, except for Pearson Type III, indicate return periods ranging from approximately 50 to 70 years. In Khorramabad, Pearson Type III exhibited the lowest performance. In Kuhdasht, with a maximum daily rainfall of 67 mm, the empirical return period is 10 years, while the mathematical distributions yield return periods between 15 and 20 years, with the GEV showing the weakest performance. At Poldokhtar and Nurabad, short statistical period, data dispersion, and bimodal distribution were observed Figure 3. Notably, the rainfall in March and April 2019 was significant, with Poldokhtar recording a maximum of 139 mm in March 2019 and Nurabad experiencing 101 mm of notable rainfall. The empirical and mathematical distributions differ at these two stations, with the difference being more pronounced in Nurabad than in Poldokhtar. Consequently, the return period for heavy rainfall at both stations is over 70

years, with the 139 mm rainfall in Poldokhtar associated with a return period of 70 to 200 years. The weakest performance is associated with Pearson Type III. Furthermore, some models exhibit less than 95% confidence and thus lack certainty. The variation in performance among different distributions, the significant range of return periods, and the uncertainty in model performance in estimating return periods are attributed to the substantial rainfall in March 2019 and the considerable dispersion of maximum daily rainfall at these stations. The best performance in Poldokhtar was associated with the Inverse Gamma distribution. The conditions in Nurabad are similar to those in Poldokhtar; however, the performance of the distributions is closer together, and there is no uncertainty. The return period for the 101 mm rainfall varies between 70 and 200 years. The discrepancies in performance between different distribution models emphasize the necessity for careful evaluation and validation of models against historical data. Moreover, the observed trends in maximum daily precipitation, particularly during the extreme events of March and April 2019, underscore the influence of climate variability and potential shifts in precipitation patterns. Figure 9 illustrates the relationship between annual maximum precipitation and return period across the study area. The graph presents a clear correlation between the magnitude of maximum precipitation events and their associated return periods, indicating how often specific levels of rainfall can be expected to occur. As shown, higher precipitation amounts correspond to longer return periods, emphasizing the rarity of extreme rainfall events. This information is vital for understanding flood risk and can assist policymakers and planners in developing effective flood management strategies.

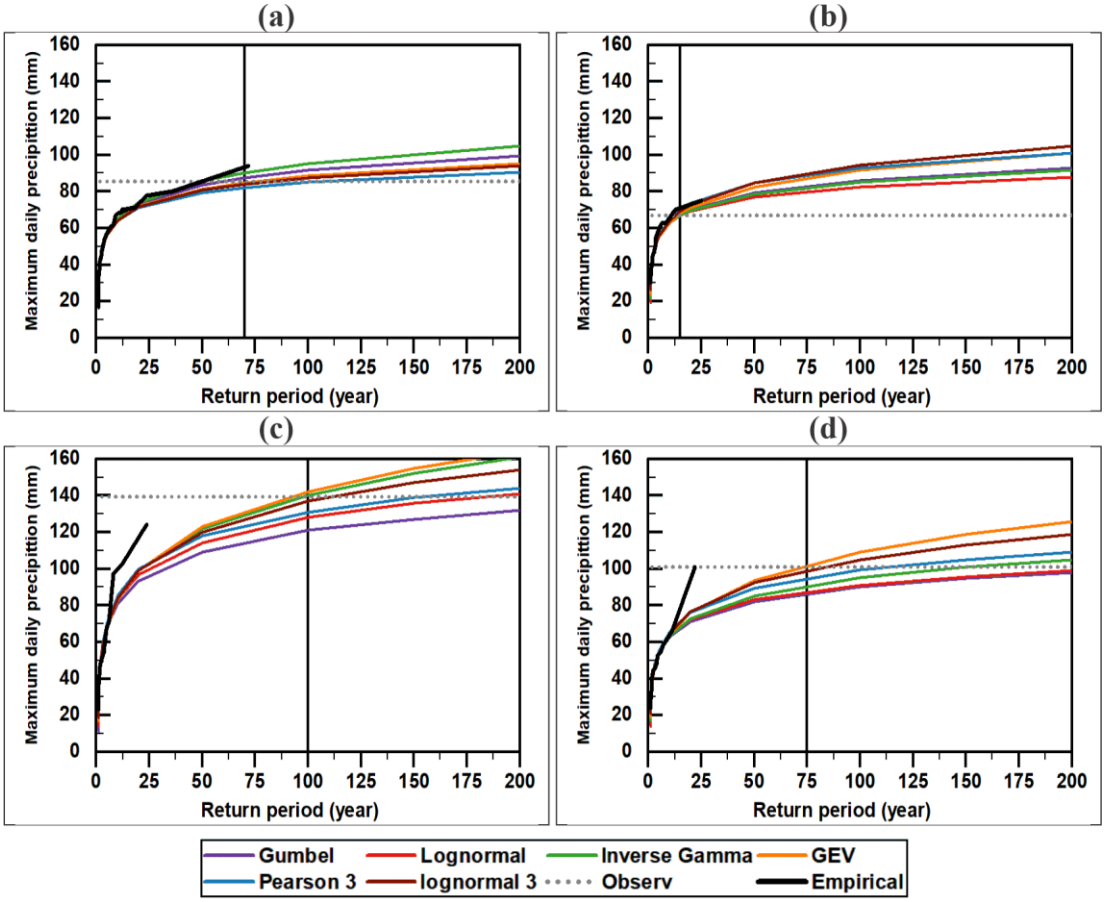


Figure 9: Empirical and statistical distributions and Maximum daily Precipitation (Observation) based on historical data at (a) Khorramabad, (b)Kuhdasht, (c) Poldokhtar and (d) Nurabad stations

In the statistical analysis, the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) were utilized to determine the best-fit curve. Table 7 demonstrates the Results of the Return Period Analysis for Selected Stations. This table presents the estimated return periods for maximum daily precipitation events at various stations, highlighting the frequency and intensity of extreme rainfall occurrences. Table 7 presents the performance scores of six statistical distributions—Inverse Gamma, Gumbel, Lognormal, Pearson3, GEV, and Lognormal3—using the for maximum precipitation analysis at four selected stations: Khorramabad, Kuhdasht, Poldokhtar, and Nurabad. Overall, across the four stations, the Inverse Gamma, Gumbel, Lognormal, Pearson Type III, GEV, and Lognormal Type III distributions demonstrated the best performance according to both criteria. Although the performance of the distributions varies by station due to the available statistical period and the highest daily precipitation recorded, the Inverse Gamma distribution performed best at three stations with shorter observational data. At the Khorramabad station, which has 72 years of statistical data, the Gumbel distribution showed the best performance. Lower scores indicate a better fit, with the Inverse Gamma distribution showing the best overall performance across most stations, particularly in Kuhdasht, Poldokhtar, and Nurabad, where it consistently ranks highest. The Gumbel and Lognormal distributions also perform well, especially at Khorramabad. Pearson3 and GEV show weaker fits, with Pearson3 achieving mixed results, performing well only in Kuhdasht. The table illustrates the variability in how different distributions capture extreme precipitation events across the region.

Table 7. Performance Scores of Statistical Distributions (BIC and AIC) for Maximum Precipitation Analysis at Selected Stations. The table lists the distribution types with their corresponding scores for the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) across the Khorramabad, Kuhdasht, Poldokhtar, and Nurabad stations. Lower scores indicate a better fit

Distribution Type	Khorramabad		Kuhdasht		Poldokhtar		Nurabad		Total Score	
	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC	AIC
Inverse Gamma	3	3	1	2	1	1	1	1	6	7
Gumbel	1	1	2	3	3	3	2	2	8	9
Lognormal	2	2	3	4	2	2	3	4	10	12
Pearson3	6	6	4	1	6	6	4	3	20	16
GEV	4	4	6	6	4	4	5	6	19	20
lognormal3	5	5	5	5	5	5	6	5	21	20

5- Conclusion

In March 2019, maximum daily rainfall exceeded the long-term average, a consequence of increased rainfall upstream that led to flooding downstream in the Karkheh basin, causing extensive damage across several provinces in western and southwestern Iran. In this study, the statistical characteristics of precipitation in the Karkheh basin were examined to determine whether the March and April 2019 rainfall events were extreme. In addition, the return period and the maximum probable precipitation (PMP) were evaluated for several stations located within the basin.

The result shows that the annual total rainfall did not exhibit a significant trend; however, maximum daily rainfall demonstrated an increasing trend, which may indicate climate change and an increase in the frequency of extreme events. The maximum precipitation events are not normally distributed across the basin. All stations exhibited positive skewness, indicating a tendency of the data toward extreme values. These visualizations offer critical insights into the rainfall patterns and the occurrence of extreme weather events in the region.

Using the percentile method, most daily rainfall events fall within the normal range, followed by heavy rainfall and then low rainfall. An important point is that heavy rainfall events have a greater contribution compared to low rainfall, meaning that in the Karkheh basin, heavy daily rainfall occurs more frequently than low-intensity daily rainfall. The highest variability in heavy daily rainfall is observed in Poldokhtar, which is mainly due to the March 2019 event with 139.1 mm of rainfall. Given its specific geographical position—located upstream and near the Jelogir hydrometric station—Poldokhtar plays a significant role in shaping flood events and runoff in the Karkheh River.

In March, and April 2019, four selected stations in the Karkheh basin experienced very heavy rainfall (within the 99th percentile). During these days, the peak runoff reached up to 1359 and 4688 m^3/s, and even on non-rainy days, the runoff exceeded the base flow average. Therefore, in March 2019, the Karkheh basin witnessed extreme and unusual rainfall in the region. Although other factors, such as land use changes and unauthorized constructions along the riverbanks, significantly contributed to flood damage across multiple provinces, rainfall was the primary factor triggering this event.

While the Gumbel distribution proved most effective for the 72-year record at Khorramabad, the Inverse Gamma distribution provided the best fit for shorter data periods, estimating return periods of 50 to 200 years for extreme rainfall events at different stations. However, at the Poldokhtar and Nurabad stations, which recorded maximum daily rainfall of 139.1 and 101 mm, respectively, in March and April 2019, the return periods were estimated to range from 70 to 200 years using six different statistical methods- six statistical distributions—Inverse Gamma, Gumbel, Lognormal, Pearson3, GEV, and Lognormal3. While the present study, based on multiple statistical methods, classified the March–April 2019 rainfall events in the Karkheh Basin as extreme precipitation, the return period of 56 years reported by Miri et al. (2023) using the Generalized Extreme Value (GEV) distribution appears to be underestimated. This is especially evident when considering that the flood return period at the Jelogir hydrometric station in the Karkheh Basin has been estimated to be 262 years Bayat-Afshary et al. (2022). The difference between the present results and Miri et al. (2023) seems to be due to the differences in the precipitation dataset. Moreover, the results of the present study indicate that the Inverse Gamma method produced the best results at stations with limited data, while the GEV method achieved lower performance scores. In addition, similar results were obtained at Nurabad, another station experiencing heavy rainfall.

The frequency factor (K_m) determine 3.50 in Karkheh Basin by Desa M et al. (2001) method. The Maximum PMP 24-h was estimated 161, and 118.8 mm in Poldokhtar and Nurabad, respectively, where they had maximum daily rainfall in March and April 2019 bases on Desa M et al. (2001) . All three PMP estimation methods, PMP24/P24, were greater than in Poldokhtar and Nuranad, this ratio was the lowest in Desa M et al. (2001) PMP estimated method. Fattahi and Habibi (2022) indicated that the Desa M et al. (2001) method provides a more reasonable estimation of the PMP, and the resulting coefficients K_m are lower compared to those obtained using the Hershfield (1961) method.

Notably, the highest daily rainfall over the long term did not occur in March or April. While the extreme rainfall events in March and April 2019—potentially linked to climate change—resulted in significant flooding and damage, other factors, such as alterations in land surface structure, particularly along riverbanks, also contributed to the increased human and financial losses. The increased occurrence of extreme rainfall events in the region as a result of climate change has been highlighted in previous studies (Fazel-Rastgar, 2020). In addition heavy to extreme rainfall events, the 2019 floods have been attributed to weak regulatory policies, insufficient oversight of environmental-hazard-prone areas (e.g., floodplain management), poor disaster-risk governance (such as lack of proper decision-making and enforcement), inadequate use of reservoir storage, and delayed implementation of flood management measures, as discussed by Seyghal et al. (2019) and Rajabizadeh et al. (2019). Overall, our research contributes to the understanding of hydrological extremes and informs strategies to mitigate flood-related damages in the Zagros Mountains, ultimately supporting climate resilience efforts in vulnerable regions.

Discussion of Uncertainties and Limitations

One of the most significant limitations of this study is the lack of long-term observational data (exceeding 30 years) in the region. This is particularly true for several stations that have recorded the highest 24-hour rainfall amounts, where the statistical period for synoptic data is less than 20 years. Consequently, analyzing the return periods of extreme rainfall events at these stations is not feasible. Additionally, the reliance on historical data introduces uncertainties related to potential changes in climate patterns over time. Such changes may affect the accuracy of extreme rainfall predictions and risk assessments, underscoring the need for continuous monitoring and the incorporation of updated datasets in future analyses. To improve the reliability of the results, the use of longer-term precipitation records is recommended, even if such data are obtained from satellite observations or reanalysis products rather than ground-based measurements.

conflict of interest

None of the authors has a conflict of interest to disclose.

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