Prediction of Flood Events from the Nekor River Discharge Using the Flood Frequential Analysis Method

Ahmed Zian[1], Lahcen Benaabidate [2], Yahya El Hammoudani [1], Khadija Haboubi [1], Fouad Dimane [1]

[1] Laboratory of Engineering Sciences and Applications, National School of Applied Sciences of Al-Hoceima, Abdelmalek Essaâdi University, Ajdir 03, Morocco
[2] Laboratory of Functional Ecology and Environment Engineering, Faculty of sciences and techniques, University of Sidi Mohammed Ben Abdellah, Fez 30500, Morocco

Abstract. This work aims to analyze the yearly most extreme release of the Nekor River monitoring station Tamellaht between 1973 and 2011 and to predict possible future events using the Flood Frequency Analysis Method (FFA). We use the four most estimated distributions that are accessible for prediction of hydrological risk: the three Log Normal, Log-Person Type III, Weibull and GAMMA distributions, and conclude that the Weibull distribution is the suitable statistical model that describe well into our data series, even though the other distributions show data adjustment. Given the Weibull dispersion, the upsides of 580.3 m3/s, 1339 m3/s and 2146.7 m3/s are for the time of return of 10, 50 and 100 years, individually, still high relying upon the semi-dry environment that wins around this region. In fact, the period of extreme returns of the 10th period which can cause dangerous flooding especially considering the mountainous characteristics of the region. The magnitude of the floods is greater because the return period is greater, which explains the semi-arid climate of this region. In addition, a simple statistical description shows that the maximum flow trend has declined over the years, reflecting a possible impact of climate change phenomena. Key words: Flood frequency analysis (FFA), semi-arid climate, Nekour watershed, maximum annual discharge, return period.

1. Introduction

Outrageous climate occasions, for example, tempests, floods and dry spells significantly affect the farming and financial areas of the nation in the word. Consequently, analysis of these events is an important part of hydrology and hydroclimatology research. The prediction of the occurrence or frequency of these events is of great interest to stakeholders. This study uses frequency analysis to explore floods and predict potential future events..

In designing hydraulic and civil infrastructure, including dams, spillways, levees, urban drainage systems, culverts, road gorges and parking lots, it is important to estimate the size of floods at a specific recurrence interval (called the T-year flood). One important aspect of flood frequency analysis (FFA) is to choose appropriate frequency distribution. Studies have shown that changes in precipitation patterns affect the magnitude, frequency and timing of floods at regional and local level [2]. In particular, the coastal regions of the Mediterranean region in the central west are severely affected by climatic and topographic conditions [3]..

Flood frequency analysis is usually based on various distributions such as Gumbel, Gamma, generalized extreme values (GEV), Pearson III (P-III), Pearson III Log (LP-III), Weibull and LN Lognormal (LN) [4, 5]. These distributions are used to analyse water frequency in different regions around the world; for example, P-III is a standard in China and Australia, LP-III in the United States and GEV in Europe [1-6]..

The primary objective of the study is to use the most commonly used distributions in the FFA, namely normal, GEV, log-Pearson type III (LP-III) and Gamma. Our methodology includes four key steps: first select a distribution and then estimate its parameters in various standard methods (Moment, Maximum Probability, L Moment, Probability Weighted Moment, and Minimum Square). In particular, we apply the maximum probability method for normal, GEV, and gamma distributions and the average method for LP-III distributions. Subsequently, we assessed the performance of these distributions, identified the most appropriate distribution, and determined the magnitude of the various return periods. Finally, we analyse the evolution and return time of frequency distributions based on the selected data series [7]..

2. Study area and Data collection

2.1. Study area

The Nekor River watershed, covering an area of 846 square kilometers, is located in the Al Hoceima region of Northern Morocco, extending from the southwestern Rif mountains to the Mediterranean coast (Fig. 1) [8]. This watershed experiences a semi-arid climate, similar to that of southwestern Europe (notably Spain and Portugal), particularly during the winter season. Its climate is shaped by the influences of the Atlantic Ocean, the Mediterranean Sea, and the Sahara [9]. Rainfall patterns in this region of Morocco are primarily governed by three factors: winter cyclonic depressions, topography, and convection. The primary contributor to the severe floods affecting the northern part of the country is torrential rainfall. Despite its location in the Rif Mountains, the watershed's slope remains below 15%, indicating a relatively uniform altitude distribution [10]. This geometric characteristic, particularly altitude, plays a crucial role in determining the design flood.

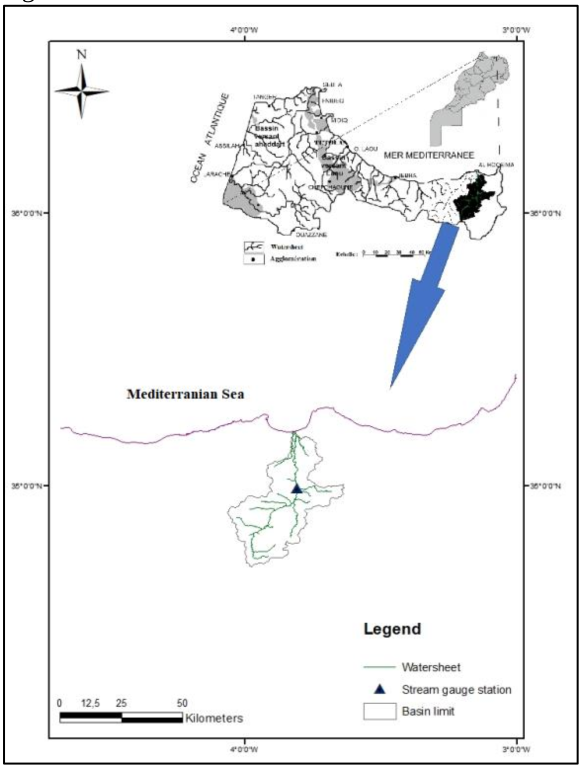

Fig. 1. The Nekor river watersheet.

2.2. Data series representation

Data for this analysis were sourced from the ABHL (Loukouss Watershed Agency), focusing on a method that captures the sample data through the instantaneous function value at specific time intervals. The measurement unit for these pulse data is cubic meters per second (L^3 T^-1). This dataset consists of instantaneously recorded annual maximum flow rates from 1973 to 2011, collected at the Tamellaht station situated at the outlet of the watershed. The recorded data correspond to a semi-arid climate region, noted for its sudden and sparse rainfall events[11].

2.3. Statistic preliminary treatment of data Series

Prior to evaluating the suitability of a statistical distribution, verifying that the dataset adheres to the Independent and Identically Distributed (IID) criteria is crucial. This means that each data point should be an independent occurrence of a random variable, all sourced from a unified statistical distribution, thereby ensuring uniformity across the dataset. Within the HYFRAN-PLUS software, several statistical tests are designed to assess the dataset for independence, stationarity, and homogeneity to ensure it meets these prerequisites [12, 13].

The process of ensuring data integrity involves three key tests: (1) the test for homogeneity ensures consistent data sources over time which is determined by the homogeneity test of Man Withney (Wilcoxon) who was originally introduced by Wilcoxon for comparing two groups of equal size [14]; Later, Mann and Whitney expanded it, making it synonymous with the Mann-Whitney U test [15]; (2) the stationarity test checks that the statistical properties of the series do not change over time. In this research, the Mann-Kendall (MK) statistical test is employed to evaluate the stationarity of the sampled data [16, 17, 18]. This test has an advantage over others thanks to their independence from assumptions about the data's distribution, making them particularly suitable for analyzing hydrometeorological time series. The MK test is favored over other nonparametric alternatives due to its ability to provide unbiased estimates of population parameters; and (3) the independence test confirms that each data point does not influence another; witch is defined by the Wald and Wolfowitz independence test [19], thereby determining the independence and stationarity within two subsets of a larger sample (n=42). Independence in this context implies the absence of any association between consecutive observations within the same group. The method involves arranging the values of each subset in ascending order and assigning a unique code to the values in each sequence. The results of the three tests are summarizing in the table1.

Table 1. Results of the statistic test of data series

Test type	Statistic value	Decision
homogeneity test of Man Withney	$\|u\| = 0.885$	we accept H0 at significance of 5% But it can be concluded that averages of the tow samples are different
Mann-Kendall	$p = 0.16786$	p>0.05, so the test is verified.
Wald and Wolfowitz independence	$u = 0.988$	we accept H0 at significance level of 5%. That is mean the observations are independent

2.4. Statistic description

The analysis of the maximal discharge curve reveals a peak flow rate of 2040 cubic meters per second (m^3/s) in October 1987, with another significant event reaching 1786.3 m^3/s in November 2003 (Fig. 2). A notable discharge of 838 m^3/s was also recorded during the dry season, specifically in August 1975. Over a 37-year period, the dataset shows that in 12 instances, flood discharges varied between 2040 to 0.307 m^3/s indicating a high severity of the floods but also with a low frequency which depend on the depth and the shape of the minor bed as well as the geological characteristics and climatic fluctuations of the area crossed..

An analysis of the trend line for maximum discharges (Fig. 2) indicates a low downward trend over the years, with a minimal coefficient of determination (R^2=0.002). This pattern suggests that the floods being studied are typical of a semi-arid climate, characterized by a high occurrence of lower annual maximum discharge rates and a less frequent occurrence of higher discharge rates. The cumulative sum curve (Fig. 3) illustrates significant fluctuations in the maximum annual discharge rates. we can distinguish at least 3 major peaks, the first in the mid-70s, the second in the late 80s, the third in the early 2000s.

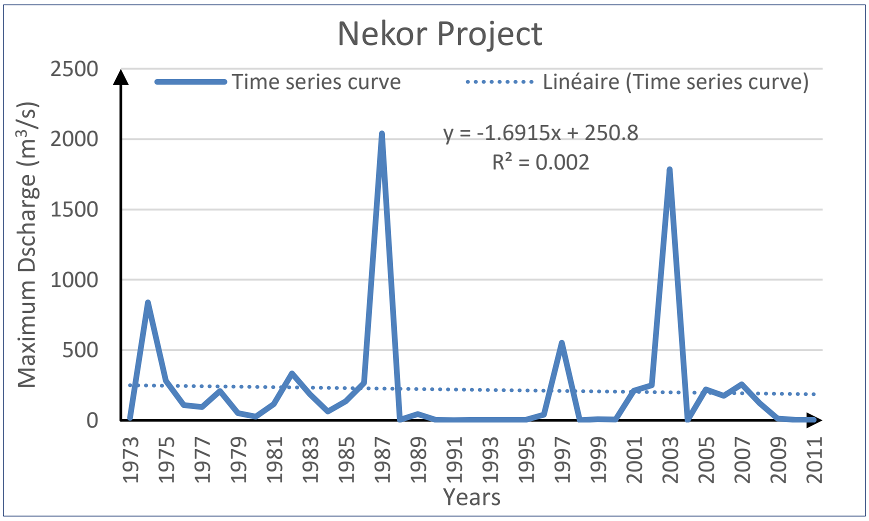

Fig. 2. The maximum Discharge curve of the Nekor Waterscheet.

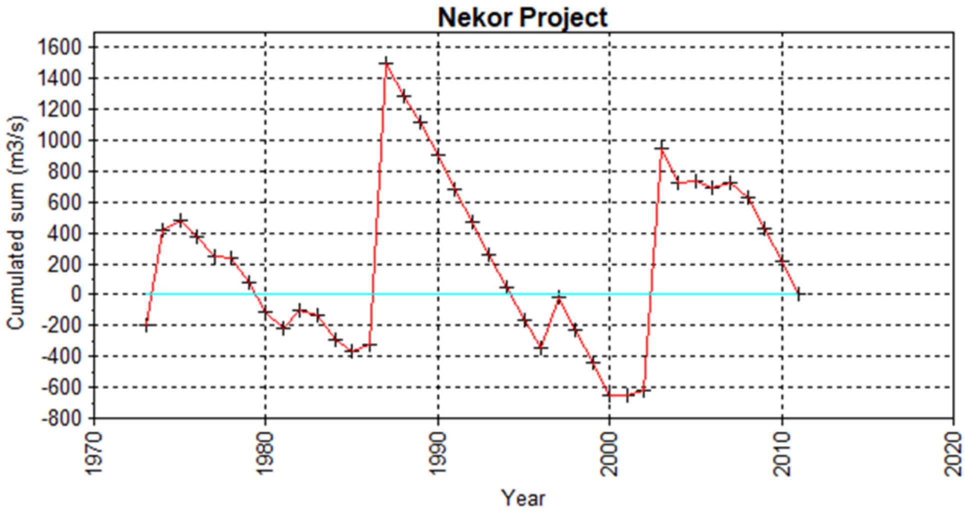

Fig. 3. Cumulative sum curves of the annual maximum discharge from the Tamellaht station

3. Probability Plotting and plotting Position Formula.

The initial step involves calculating the exceedance probability for each data point, employing the Hazen empirical formula: p = (m $^{-0.5}$) / N [20]. To implement this method, one must first sort the data set (with N entries) in descending order based on magnitude, assigning each entry a rank number (m). The highest data point is assigned m = 1, the next highest m = 2, and so on, until the lowest data point receives m = N. Subsequently, the Cunnane formula is applied to calculate the exceedance probability (p) for every data point in the series, leading to the determination of p and consequently T (calculated as 1.67N + 0.33) [20]. The data's magnitudes are then plotted against their respective exceedance probabilities to create the probability plot, with the flood magnitudes, exceedance probabilities (P), and return periods (T) showed in figure 4. It should be noted that a line of best fit is applied to the data points, described by the equation Q = 30.724T + 44.085 (with an R^2 of 0.81). However, three exceptional values (2040 m^3/s, 1786.27 m^3/s, and 838 m^3/s) do not align with this trend line. The return periods of 10 years or shorter, flood magnitudes range from 552.4 m^3/s to 0.30 m^3/s. For return periods of 10, 50, and 100 years, the flood magnitudes are estimated at 351.3 m^3/s, 1580.^{3} m3/s, and 3116.5 m^3/s, respectively.

If we ignore the last point, these findings suggest a linear relationship between flood magnitude and return period, highlighting that even at a 10-year return period, a flood magnitude of 351.3 m3/s could potentially lead to significant flooding.

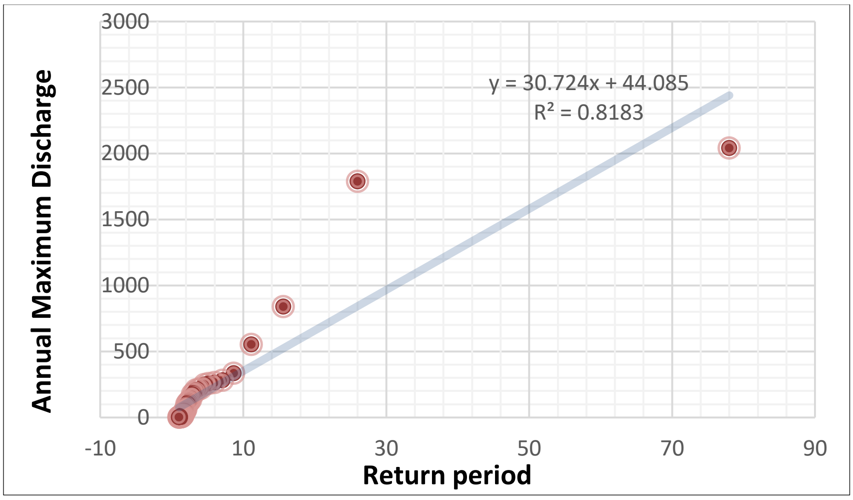

Fig. 4. Flood frequency plot for Data series study.

4. Flood Frequential analysis (FFA)

Through the process of probability plotting, it has become apparent that outcomes may manifest either within a single day or over a span of time, such as in the case of severe storms and flash floods. These hydroclimatic extremes significantly affect the hydrological system. The primary goal of conducting a flood frequency analysis (FFA) is to derive accurate estimates of extreme quantiles and to ascertain the likelihood of surpassing specific event magnitudes.

This approach is underpinned by extreme value theory (EVT), which primarily relies on the asymptotic principles outlined in the Fisher-Tippett theorem [21]. Incorporating historical data into frequency analysis enhances the precision of quantile estimates for events with long return periods.

The core procedures of frequency analysis encompass selecting an appropriate probability model and estimating parameters from observed data. Traditionally, this involves fitting various theoretical probability functions to the data using different methods to estimate the parameters of potential distribution functions. Subsequently, statistical criteria such as the Akaike Information Criterion (AIC) [22], Bayesian Information Criterion (BIC) [23], or Hannan-Quinn Criterion (HQ) are employed to identify the most suitable model [24]. Nonetheless, these criteria are grounded in the likelihood function, tending to prioritize the distribution's central portion, which encompasses a majority of the observations. Given that FFA aims to estimate quantiles associated with rare events (indicating a low probability of exceedance), it's crucial to assess model suitability based on the tail behavior of the distribution, focusing on extreme values rather than the central tendency.

4.1. Theoretical framework

Frequency analysis is a popular method for studying hydroclimatic data, because it can be assimilated as periodic but mostly stationary signals. For this reason, The frequency distribution functions that are utilized in this domain is therefore[20]:

$$x_T = \bar{x} + KS \qquad (1.1)$$

x_T : greatness of the hydrologic variable with a return period.

$\bar{x}$: Mean value,

S : Standard deviation value

K : frequency factor.

For the purpose of predicting extreme events, various probability distribution functions can be utilized. The Log-Normal, Weibull, Log Pearson type III and Gamma are applied in this study. Using those distribution functions, a sample of hydrologic data is tested to determine the best probability.

4.1.1.Three parameter Log Normal distribution (LN3).

When a hydrological variable (X) sticks to a normal dispersion, its recurrence factor, K, matches with its standard ordinary variate, Z. According to Equation (1.1), K is defined as K = (x_T - $\bar{x}$) / S, where $\bar{x}$ is the mean, S is the standard deviation, and x_T is the value for a specific return period. The standard normal variate Z is basically matched by this expression for K. Thus, The identification of a flood, for example, is equivalent to calculating its exceedance probability and the corresponding value of Z from the standard table. The magnitude of the flood can derived from equation (1.1) by using the value Z which a frequency factor K.

The 3-parameter lognormal distribution is used to describe variables where the logarithm of (x - a), with "a" being a shift parameter and the logarithm base e, follows a normal distribution. In this scenario, x represents the hydrological variable, and (x - a) is termed the shifted variable. This distribution is versatile, allowing the logarithm of any linear transformation of x to be normally distributed. The shift parameter "a" is determined based on the statistical characteristics of x and can assume positive, zero, or negative values.

The probability density function lognormal distribution can be articulated as follows:

$$f(x) = \frac{1}{(x-a)c\sqrt{2\pi}} \exp\left(\frac{-[\ln(x-a)-b]^2}{2c^2}\right) \qquad (1.2)$$

where:

(X): Random variable
“a”: lower boundary quantity,

“b”: shape parameter

“c”: scale parameters.

(y) : the mean of the distribution witch is equal to the parameters “b” and “c^2”,
(s): variance of In (x-a).

When the random variable (X) is moved by “a” The two-parameter lognormal distribution (LN2) changes to the three-parameter log-normal distribution (LN3). (x-a) addresses a displaced variable. The normalized variable u is obtained as follows:

$$\mu = \frac{\ln(x-a)-b}{c} \quad (1.3)$$

The cumulative distribution function of the TPLN distribution can be obtained by integrating the equation (1.2):

$$f(x) = \int \frac{1}{(x-a)c\sqrt{2\pi}} \exp(\frac{-[\ln(x-a)-b]^2}{2c^2}) \quad (1.4)$$

In this study, we find: $a = -271.146$, $b = 5.89833$; and $\mu = 0.764485$.

Adequacy using chi-squared test show that we accept H0 at significance level of 5% with p=0.93.

4.1.2. Gamma Distribution

There are 3 types of gamma distribution depending on the number of parameters considered (one, two or three parameters). In our study, we will use the Gamma distribution with a tow parameter. The PDF of the two parameters Gamma model is written by:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\alpha/\beta}\ ;\ x \geq 0 \quad (1.5)$$

the gamma distribution in hydrology, describe well the extreme events like flood since it having only positive value who can find in hydrological data series [13, 25].

The maximum likelihood estimation method [26], for the tow parameters used in this study give: $\alpha = 0017552$ and $\lambda = 380821$. The adequacy using Chi-squared show that we accept H0 hypothesis at significance of 5% with $\chi 2= 6.74$.

4.1.3. Log-Pearson Type III Distribution

The log-Pearson type III distribution is one of the seven different types of Pearson distribution and it also popularly used to analyze a frequency of flood. It is deducted from Pearson distribution by a logarithmic transformation Y=LnZ∽P⟺Z∽LP. We can look at a random base "a". The probability density function of Pearson type III distribution with three-parameter could be as follows:

$$fX\ (x) = \frac{\lambda\beta\ (x-\varepsilon)\beta-1e-\lambda(x-\varepsilon)}{\Gamma(\beta)} \text{ for } x \geq \varepsilon \quad (1.6)$$

Where: (X) is random variable,

α and β are the scale and shape parameter, respectively

x -ε has the lower bound

In practice, using HYFRAN software, the e (Neperian logarithm) or base 10 (decimal logarithm) is used. The PDF of the statistic law $LP(m, \alpha, \lambda)$ can be inferred from that of Pearson Type 3 [27] and is given by:

$$f(x) = \frac{|\alpha|}{\Gamma(\lambda)} + e^{-Lnz-m}[\alpha(Lnz - m)]^{\lambda-1}.\frac{1}{z} \quad (1.7)$$

We must have: $\alpha(Lnz - m) \geq 0$

$\alpha > 0$ $\quad$ $Lnz > m$ $\quad$ $z \geq e^{m}$

$\alpha < 0$ $\quad$ $Lnz > m$ $\quad$ $0 \leq z \leq e^{m}$

The non-centered moments are given by:

$$\mu'_r = \frac{e^{mr}}{\left(1-\frac{r}{\alpha}\right)^{\lambda}} \quad (1.8)$$

With $\left(1 - \frac{r}{\alpha}\right) > 0 \rightarrow \frac{r}{\alpha} < 1$

if $\alpha > 0$, $r < \alpha$, i.e moment exist up to order $r_0 = [\alpha]$

If $\alpha < 0$, $r > \alpha$, which is always true for $(r > 0)$ because $\alpha < 0$.

There are no comprehensive statistics for the LP distribution. Therefore, the method of maximum likelihood is no optimal. Several estimated methods have been proposed by Bobée and Ashkar [13]. In this study, the method of moments (BOB) [27] is used.

The first 3 non-centered moments of the LP3 population (parameter functions, Eq.1.10) and their estimates obtained from the sample of observed values are equal: $(x_1 \ldots x_i \ldots x_N)$

$$\frac{e^{mr}}{\left(1-\frac{r}{\alpha}\right)^{\lambda}} = \frac{1}{N}\sum_{i=1}^{N} x_i^r \qquad r=1, 2, 3 \tag{1.9}$$

The resolution of this system is described in [12-25].

The estimated parameters in this study are:

$$\alpha = -1.04199, \lambda = 2.47882 \text{ and } m = 3.59186$$

The adequacy for our data series is follow: $X^2 = 11.67, p = 0.0200$, degrees of freedom = 4 and Number of class = 8. So, we can reject Ho at significant 5% but we accept at significance level of 1%.

4.1.4. Weibull Distribution

When the parent distribution is limited and does not have sufficiently large values, the weibull law is appropriate. Although it is used for the minimum data corresponding to drought, it can sometimes describe floods that occur with particular data [19] . The Probability density function (fX (x)) and the Cumulative density function (FX (x)) are given by:

$$fX(x) = \alpha x^{\alpha-1}\beta^{-\alpha} \exp[-(x/\beta^{-\alpha}]; \tag{1.10}$$

$$FX(x) = 1 - \exp[-(x/\beta^{\alpha}] \tag{1.11}$$

Where: X , random variable ($x \geq 0$)
α and β : respectively the scale and the position parameters ($\alpha, \beta > 0$).
In this study, we used the Moment method to calculate the parameters who can give best fit, we find: $\alpha = 124.467$, and $\beta = 0.54175$

Adequacy is also verified by Chi-squared test, we accept H0 at significant level of 5%.

5. Results and discussions

5.1. Adequacy

For choosing the sufficient statistic model, it is generally helpful to make suspicions about the populace required by utilizing speculation testing. The Ki square test is one of the most broadly utilized likelihood appropriations. The PDF (Probability density function) and CDF (Cumulative Density Function) of the chi-square distributions are as follows is defined as:

$$f_{x2}(x) = \frac{x^{\left(\frac{\nu}{2}-1\right)} e^{\left(-\frac{x}{2}\right)}}{2^{\left(\frac{\nu}{2}\right)}\Gamma\left(\frac{\nu}{2}\right)} \qquad x, \nu > 0 \tag{2.1}$$

$$f_{x2}(x) = \frac{\gamma\left(\frac{\nu}{2},\frac{x}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)} \qquad x, \nu > 0 \tag{2.2}$$

Where: (X) random variable according to the sum of squares,

ν is a degree of freedom ($\nu > 0$).
γ (p, q) is a lower gamma statistic model that is defined as:

$$\gamma(p, q) = \int_0^q t^{p-1} e^{-t}\, dt \tag{2.3}$$

For considering the random variables Z1, Z2, . . ., Zν who follow normal distribution, then:

$$Y = \sum_{i=1}^{\nu} Z_i^{\,2} \tag{2.4}$$

The table 2 illustrates the statistics result and conclusion for the Chi-squared test according to the different used distributions applied to the FFA. This test highlights that, all the distributions are adequate for the corresponding Data series. The adequation is verified for Log Pearson Type III at a significance of 1%. It is verified for Three parameter Lognormal by applied Shapiro-Wilk test with the p value SW= 0.94 and p= 93.

Table 2. The statistics result for the Chi-squared test

	χ2	**p-value**	**Degree of freedom**	**Number of classes**	**Conclusion (at significant level of 5%)**
Three-parameter Log Normal	-	0.02	4	8	We reject H0

Log-Pearson type III	11.67	0.02	5	8	We accept H0*
Gamma	6.74	0.24	5	8	We accept H0
Weibull	5.51	0.35	5	8	We accept H0

* Accepted at significant level 1%

Probability distribution papers are utilized to assess if the observed data aligns with any of the preselected distributions. Specifically, for the dataset comprising maximum flood observations (X), the mean and standard deviation for various distributions are computed and presented in Table 3, revealing uniformity in mean values across all distributions.

Table 3. Mean and standard deviation for each distribution

Distribution	Mean(m^3/s)	Standard deviation(m^3/s)
Three Log Normal	217	435
Log-Pearson type III	217	429.3
Gamma	217	351.6
Weibull	217	435

Fig. 5 illustrates the fitting of the maximum flood data series to various distributions, delineated by confidence intervals (CI) represented by two blue lines at the extremes, corresponding to the probability measures. For the curves representing the theoretical 3-parameter log-normal, Log Pearson Type III, and Weibull distributions in Fig. 5, many points deviate from the distribution curves especially the last two values. Therefore, the data series is considered incompatible with these distributions.

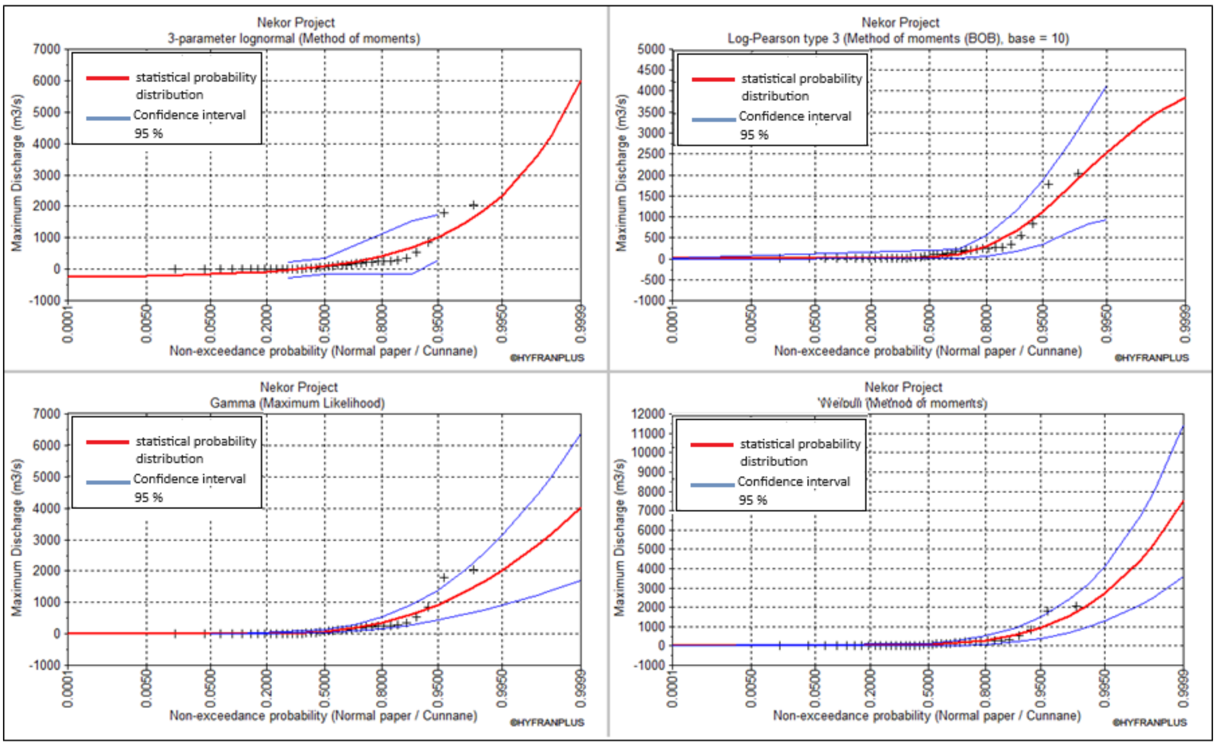

Fig. 5. Non-exceedance probability by the Different Distributions.

However, the Weibull distribution stands out, with only the last two points deviating from the distribution curve. This indicates that this distribution is the most appropriate model to describe the data set. Thus, the annual maximum discharge data from tamellaht station is best represented by a persistent likelihood conveyance. This is supported by the sample mean, which suggests a continuous, positively skewed distribution of non-negative values, or a mode situated at zero, as depicted in Fig. 6.

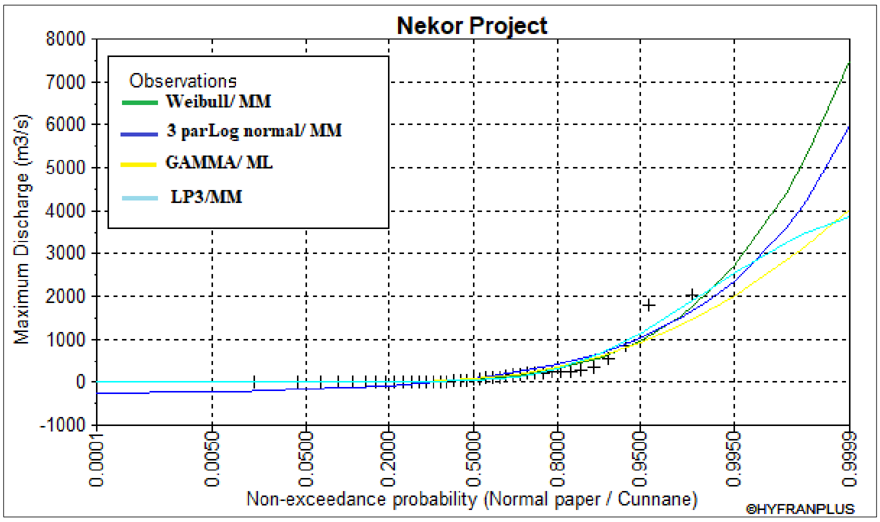

Fig. 6. Comparison of the W, 3LN, G and LP3 fits for the annual peak flood at Nekor River.

5.2. Return Period

Fig. 7 presents a comparative analysis of the outcomes across various return periods for each distribution under consideration. This comparison visually demonstrates that there is no model that seems close to the empirical data, particularly evident in the trend of the values of the return period greater than 100, which reflects the trend observed in the real data. However, it is noticed that almost all the models are close to the empirical data for values of the return period of less than 10 years. This results shows that it is difficult to describe the instantaneous rainfall for very long return periods probably because of the permanent fluctuations in rainfall..

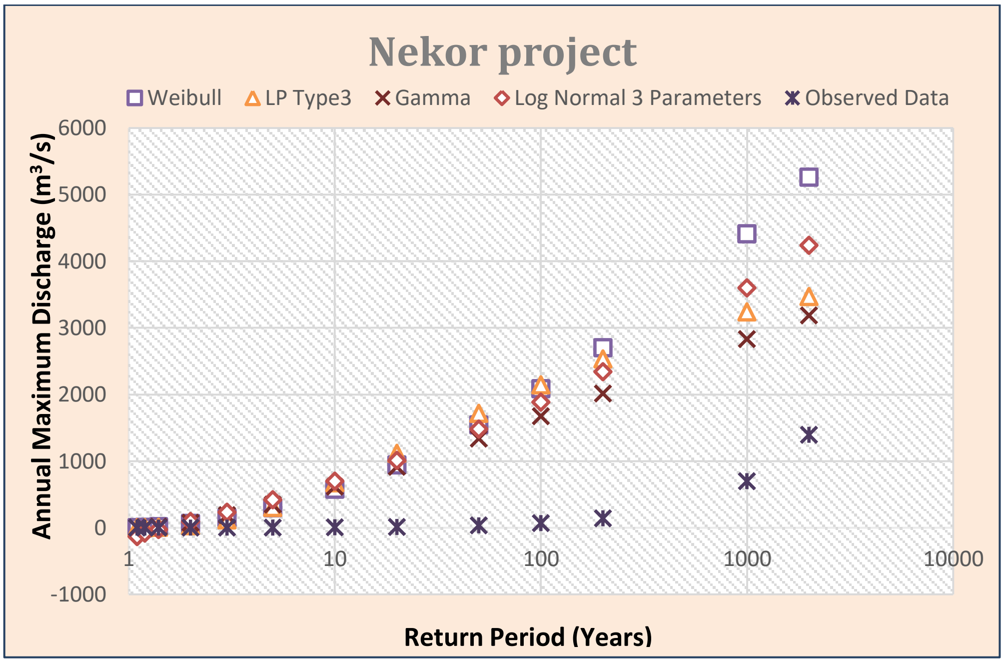

Fig. 7. Return period results obtained by different fits for the annual peak flood at Nekor River.

Table 4 offers a detailed comparison of the results obtained for all the distributions applied in this frequency analysis, emphasizing that the Weibull distribution produces the closest results with the empirical observations. Specifically, a flood magnitude of 580.3 cubic meters per second (m^3/s) predicted by the Weibull distribution for a 10-year event is considered exceptionally high, which raises concerns about a potential flood at a short duration, given the mountainous terrain of the Nekor River watershed.

Table 4. Correlation of return period results of 10, 50, and 100 years got by various distributions

Annual maximum discharge (m^3/s)	**Return Period (years)**		
	10	50	100

Plotting position (Hazen Formula)	351.3	1580.3	3116.5
3Log Normal distribution	700	1481.2	1887.3
Log-Pearson Type III distribution	673.2	1719	2146.7
Weibull distribution	580.3	1339	2086
Gamma distribution	618	1150	1672.1

6. Conclusion

The Flood Frequency Analysis (FFA) of the annual maximum flow data collected at the downstream gauging station of the Nekor River from 1973 to 2011 reveals interesting findings. Although the mean values across various distributions analyzed remain consistent, the Weibull distribution distinguishes itself with a lower standard deviation compared to others despite the fact that this trend is not well visualized. However, when examining the graphical representation of the probabilities for each distribution, no distribution seems to be close to the empirical value for return periods greater than 100 years. Whereas for return periods of less than 10 years, all distributions adjust to the observed values. the value as close to the empirical data of the Weibull model for a return period of 10 years (580.3 m3 / s) remains severe and could generate a potential risk of flooding.

This is of significant concern due to the potential for severe flooding, exacerbated by the mountainous terrain of the area. Furthermore, the analysis indicates that flood magnitudes increase with longer return periods, aligning with the region's semi-arid climate characteristics. Additionally, a preliminary statistical overview suggests a decreasing trend in maximum discharge over the analyzed period, hinting at the possible influences of climate change.

Conflict of interest

The author affirms that no conflicts of interest exist concerning the publication of this manuscript. Moreover, all ethical considerations, encompassing plagiarism, informed consent, misconduct, data fabrication and falsification, simultaneous or duplicate publication and submission, and redundancy, have been fully adhered to by the authors.

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