

14 **ABSTRACT**

15 Extreme hydrological events, such as floods and droughts, are one of the natural disasters
16 that occur in several parts of the world. They are regarded as being the most costly natural
17 risks in terms of the disastrous consequences in human lives and in property damages. The
18 main objective of the present study is to estimate flood events of Abiod wadiat given return
19 periods at the gauge station of M'chouneche, located closely to the city of Biskra in a semi-
20 arid region of Southern-East of Algeria. This is a problematic issue in several ways, because
21 of the existence of a dam to the downstream, including the field of the sedimentation and the
22 water leaks through the dam during floods. The considered data series is new. A complete
23 frequency analysis is performed on a series of observed daily average discharges, including
24 classical statistical tools as well as recent techniques. The obtained results show that the
25 Generalized Pareto distribution (GPD), for which the parameters were estimated by the
26 maximum likelihood (ML) method, describes the analyzed series better. This study also
27 indicates to the decision-makers the importance to continue monitoring data at this station.

28 **Key words** : Frequency analysis; Peaks-Over-threshold ; Generalized Pareto distribution
29 ;Threshold selection ; Flood discharges ; Extremequantiles; Biskra ; Algeria.

30

31 **Introduction**

32 The study of floods is a subject which arouses more and more interest in the field of water
33 sciences. In spite of their low rainfall, the basins of the arid and semi-arid areas represent a
34 hydroclimatic context where the overland flows phenomena are significant and feed a network
35 of very active wadis. The activity of these wadis is far from being negligible from the flood in
36 terms of their frequency and intensity. One observes on these rivers exceptional flows which
37 sometimes, surprise by their magnitude[19]. The Abiod wadi, in the area of Biskra, is a very
38 representative river of these basins. Moreover, the existence of Foug El Gherza dam to the
39 downstream for the irrigation of the palm plantations makes the area more sensitive with regard
40 to the floods. The flood events of the years 1963, 1966, 1971, 1976 and 1989 remain engraved
41 in the memory of the inhabitants. The flood event of 11- 12th September 2009 was one of the
42 historic floods in the Zibans area[7]. It rains 80 mm in 24 hours, while the annual total of Biskra
43 city reaches 100 mm. The damage were 9790 palm trees, 164 flooded houses, 744 destroyed
44 greenhouses, 200 hectares of lost cultures. The last flooding at the time of this drafting paper
45 is that produced in October 29th 2011. All the populations living downstream of the Foug El
46 Gherza dam were evacuated. The floods mainly occur in September and October and especially
47 originate from exceptional storm events.

48 Describing and studying these situations could help in preventing or at least reducing severe
49 human and material losses. The strategy of prevention of flood risk should be founded on
50 various actions such as risk quantification. On this aspect, various methodological approaches
51 can contribute to this strategy, among which flood Frequency Analysis (FA). Frequency
52 analysis of extreme hydrological events, such as floods and droughts, is one of the privileged
53 tools by hydrologists for the estimation of such extreme events and their return periods. The
54 main objective of FA approach is the estimation of the probability of exceedance $P(X \geq x_T)$,

55 called hydrological risk, of an event x_T corresponding to a return period T [16]. This process is
56 accomplished by fitting a probability distribution F to large observations in a data set. Two
57 approaches were developed in the context of extreme value theory (EVT). The first one, usually
58 based on the generalized extreme value distribution (GEV), describes the limiting distribution
59 of a suitably normalized annual maximum (AM) and the second uses the generalized Pareto
60 distribution (GPD) to approximate the distribution of Peaks-Over-Threshold (POT). For more
61 details regarding this theory and its applications, the reader is referred to textbooks such as
62 Embrechts et al.[24], Reiss and Thomas[51], Beirlant *et al.*[6] and de Hann and Ferriera [18].

63 Many FA models should be tested to determine the best fit probability distribution that describes
64 the hydrologic data at hand. Specific distributions are recommended in some countries, such as
65 the Log-normal (LN) distribution in China[10]. In the United States, the Log-Pearson type 3
66 distribution (LP3) has been, since 1967[44], the official model to which data from all
67 catchments are fitted for planning and insurance purposes. By contrast, the United Kingdom
68 endorsed the GEV distribution[45, 46] up until 1999. The official distribution in this country is
69 now the generalized logistic (GL), as for precipitation in the United States[59]. There are
70 several examples where a number of alternative models have been evaluated for a particular
71 country, for example Kenya[43], Bangladesh[35], Turkey[5] and Australia [58]. Nine
72 distributions were used with data from 45 unregulated streams in Turkey by Haktanir[26] who
73 concluded that two parameter Log-normal (LN2) and Gumbel distributions were superior to
74 other distributions. Recent research was conducted by Ellouze and Abida[23] in ten regions of
75 Tunisia. They found that the GEV and GL models provided better estimates of floods than any
76 of the conventional regression methods, generally used for Tunisian floods. Rasmussen *et*
77 *al.*[50] reveals that the POT procedure is more advantageous than the AM in the case of short
78 records. Lang *et al.*[40] develop a set of comprehensive practice-oriented guidelines for the use
79 of the POT approach. Tanaka and Takara[55] has examined several indices to investigate how

80 to determine the number of upper extremes rainfall best for the POT approach.

81 In the Algerian hydrological context, during the last two decades many authors have used
82 several approaches to study the associated risks. Recently, Hebal and Remini[29]studied flood
83 data from 53 gauge stations in northern Algeria, between 1966 and 2008. They found that 50 %,
84 25 % and 22 %of the samples follow respectively the Gamma, Weibull and Halphen A
85 distributions. Bouanani [12]performed a regional flood FA in the Tafna catchments and
86 concluded that the AM flows fit better to asymmetric distributions such as LP3, Pearson 3 and
87 Gamma. The FA was also used in the sediment context by Benkhaled et al. [8]where the LN2
88 distribution was selected in the case of the same station considered in the present study, i.e.
89 M'chouneche gauge station on Abiod wadi.

90 To the best knowledge of the authors, apart from Benkhaled et al. [8], the flood FA approach
91 has not yet been performed on data collected at this station. The primary aim of this paper is to
92 perform a FA to the Abiod wadi flow data by the POT approach, based on GPD approximation
93 [30].In methodological terms, all the steps constituting FA are performed from data
94 examination to risk assessment including hypotheses testing and model selection. Due to the
95 high importance of the latter and its impacts, more recent techniques are employed to select the
96 appropriate distribution that fit better to the tail. A relatively large number of known
97 distributions fit well the center of the data whereas the focus in FA is on the distribution tail.
98 To this end, tail classification and specific graphical tools are employed, see El Adlouni et al.
99 [22] for more technical details.

100 The paper is organized as follows. In Section 2, the study area and the data set are briefly
101 described. Section 3 is devoted to the FA methodology. The results of the study are presented
102 and discussed in Section 4. Concluding remarks are reported in Section 5.

103

104 **1. Study area and data**

105 In this section, we present the region where the site of interest is located, followed by a
106 description of the available data.

107 *1.1 Study Area*

108 The Abiod wadi watershed, with an area of 1300 Km², is located in the Aurès massif in the
109 southern east of Algeria in North Africa (Figure 1). It is part of the endorheic watershed Chott
110 Melghir. The wadi length is 85 km from its origin in the Chelia (2326 m high) and Ichemoul
111 (2100 m high) mountains. After crossing Tighanimine, the wadi gradually flows into the
112 canyons of Ghoufi and M'chouneche gorges, and then opens a path to the plain until the
113 Saharian gorge Foumel Gherza. The valley of the wadi is mainly composed of sedimentary
114 rocks, comprising alternating limestone, marl, soft sediments (sandstones, conglomerates) and
115 some evaporates (gypsum) dated of Paleogene.

116 The watershed is characterized by its asymmetry, a mountainous area in the north to over 2000m
117 (Chelia) and another low area in the south (El Habel 295 m). The relief is rugged with slopes
118 ranging between 12.5% and 25% for half of the area, and from 3% to 12.5% for another 40%
119 of the area. Land cover is a mix of rocky outcrops, highly eroded soil, sparse vegetation, a few
120 forests, crops, gardens and pastures [27]. In the orographic and hydrographic points of view,
121 Abiod wadi is characterized by two distinct climatic regions: the Aurès, where rainfall averages
122 450 mm/year, and the Sahara plain with mean rainfall 100-150 mm/year. The climate of Abiod
123 wadi watershed is thus semi-arid to arid. Along Abiod wadi to the Foug El Gherzadam there
124 are six rainfall stations, and one hydrometric station located 18 km upstream of the dam, as
125 shown in Figure 1, which was damaged during the floods of 1994-1995 and it is not operational
126 since.

127 The choice of this station was made on the basis of climatic context of the study area. It is the
128 only station on the studied basin and it is rather representative of the whole south-east region
129 in Algeria, which is arid to semi-arid. Also, the size of the series used shows the interest of the
130 FA application.

131 *1.2 Data Description*

132 The data set used in this study is provided by the National Agency of Hydraulics Resources
133 (ANRH) of Biskra and it is the first time to be considered and studied. It consists of the daily
134 average discharges Q_1, \dots, Q_N (with $N = 8034$), collected at the gauge station of M'chouneche
135 over 22 years from 1972 to 1994.

136 Note that the IACWD Bulletin 17B [1] suggests that at least 10 years of record are necessary
137 to warrant a statistical analysis. For instance, Tramblay et al. [57] used a minimum of 10 years
138 of daily data. The short data size can affect the choice of distributions, the quantile estimations,
139 particularly those corresponding to large return periods and the extent of confidence intervals.
140 The size of the used data in the present study is relatively large, to perform a FA, as in a number
141 of similar studies[15].

142 **2. Methodology**

143 In this section, after defining the type of series to be analyzed, namely the POT series, we briefly
144 present the required elements to perform a hydrological FA. The latter is a statistical approach
145 of prediction commonly used in hydrology to relate the magnitude of extreme events to a
146 probability of their occurrence[16]. It allows, for the selected station, to estimate the flood
147 quantiles of given return periods. In general, FA involves four main steps:

- 148 (i) characterization of the data and determination of the usual statistical indicators, such as
149 the mean, the standard-deviation, the coefficients of skewness (Cs), kurtosis (Ck) and

- 150 variation (Cv) and detection of outliers,
- 151 (ii) checking the basic hypotheses of FA, i.e. homogeneity, stationarity and independence,
- 152 applicability on the studied data set,
- 153 (iii) fitting of probability distributions, estimation of the associated parameters and selection
- 154 of the best model to represent the data, and
- 155 (iv) risk assessment based on quantiles or return periods, [e.g. 11, 14, 26, 49].

156 *3.1. Peaks Over Threshold Series*

157 The data to be extracted and then used in this approach consist in the observations that exceed

158 a selected relatively high threshold u . Let Q represent the daily average discharge and denote

159 by N_u the number of discharges exceeding u . Then, the sample of excesses is defined as

$$160 \quad \left\{ E_j = Q_{i_j} - u \quad \text{s.t.} \quad Q_{i_j} > u ; j = 1, \dots, N_u \right\}.$$

161 In this approach the selection of an appropriate threshold is crucial. This approach is useful and

162 has some advantages compared to the AM one, even though the latter is widely used. It is of

163 particular interest in situations where the AM could not perform well especially in situation

164 with little extreme data or the extracted extremes by AM cannot be considered as extremes in

165 a physical or hydrological meaning.

166 *3.2.1. GPD Approximation*

167 Statistically, the distribution of the POT series E_1, \dots, E_{N_u} , can be determined by making use of

168 the GPD which is a cdf $G_{\gamma, \sigma}$ defined, for $x \in S(\gamma, \sigma) := [0, \infty)$ if $\gamma \geq 0$ and $[0, -\sigma / \gamma)$ if $\gamma < 0$,

169 by:

170
$$G_{\gamma,\sigma}(x) = \begin{cases} 1 - \left(1 + \gamma \frac{x}{\sigma}\right)^{-1/\gamma}, & \gamma \neq 0, \\ 1 - e^{-x/\sigma}, & \gamma = 0, \end{cases} \quad (1)$$
 where $\gamma \in R$ and $\sigma > 0$ are respectively shape and

171 scale parameters[31].

172 Let $F_u(x) = P(Q - u \leq x | Q > u)$ denote the excess cdf of Q over a given threshold u . Then, we
 173 have the following result:

174
$$\lim_{u \rightarrow q_F} \sup_{0 < x < q_F - u} |F_u(x) - G_{\gamma,\sigma(u)}(x)| = 0, \quad (2)$$

175 where q_F is the right end point of the cdf F . This result, due to Balkema and de Haan[4] and
 176 Pickands [48], is one of the most useful concepts in statistical methods for extremes. It says that
 177 for large threshold u , the excess cdf F_u is likely to be well approximated by a GPD.

178 3.2.2. Threshold Selection

179 In order to obtain the asymptotic result in(2), the threshold u should be large enough which has
 180 as a consequence a satisfactory GPD approximation. The choice of the threshold is a crucial
 181 issue in the POT procedure. Indeed, selecting a threshold that is too low results in a large bias
 182 in the estimation, whereas taking one that is too high yields a big variance[24, section 6.4 and
 183 6.5]. Hence, a compromise between bias and variance is to be found. To this end, one can
 184 minimize the asymptotic mean squared error, which is composed by the bias and variance.
 185 Furthermore, several graphical procedures are available to select u , such as the mean residual
 186 life (MRL), threshold choice (TC) and dispersion index (DI) plots. On the other hand, the choice
 187 of u can be based on physical considerations, e.g. by identifying the flood level of the river of
 188 interest. For a survey of the main selection procedures, see e.g. the paper of Lang et al [40].

189 3.2. Exploratory Data Analysis

190 The first step allows to check the data quality and to screen the data to avoid outlier effects. It
 191 also permits to obtain prior information, e.g. the shape, regarding the distribution to be selected.
 192 The presence of outliers in the data can have an important effect and causes difficulties when
 193 fitting a distribution[3]especially on the distribution upper part. The Grubbs and Beck[25]
 194 statistical test, based on the assumption of normality data, is designed to detect low and high
 195 outliers. In the case where the original data are not normal, they should be appropriately
 196 transformed. According to Section 1.8.3 in[49], this test is based on the following quantities:

$$197 \quad x_H = \exp(\bar{x} + k_n s), \quad (3)$$

$$198 \quad x_L = \exp(\bar{x} - k_n s), \quad (4)$$

199 where \bar{x} and s are respectively the mean and standard deviation of the natural logarithms of the
 200 sample, and k_n is the Grubbs-Beck statistic tabulated for various sample sizes and significance
 201 levels by Grubbs and Beck [25]. For instance, at the 10% significance level, the following
 202 approximation is used

$$203 \quad k_n = -3.62201 + 6.28446n^{1/4} - 2.49835n^{1/2} + 0.491436n^{3/4} - 0.037911n, \quad (5)$$

204 where n is the sample size.

205 The observations greater than x_H are considered to be high outliers, while those less than x_L
 206 are taken as low outliers.

207 *3.3. Testing Independence, Stationarity and Homogeneity*

208 Three basic assumptions are required to correctly apply FA of extreme hydrological events,
 209 namely independence, stationarity and homogeneity of the data[11]. To verify these
 210 assumptions, three tests are widely used in the literature. The Wald-Wolfowitz test is employed

211 for the independence, the homogeneity test of Wilcoxon is applied to check whether the data
212 come from the same distribution or not and the Mann-Kendall test allows to verify stationarity
213 of the data, i.e. the series does not present a trend over time. These three tests have the advantage
214 of being non-parametric and are widely used in hydrological FA. In other words, they do not
215 require any prior knowledge on the distribution of the data.

216 *3.4. Parameter Estimation and Model Selection*

217 The choice of the appropriate model is one of the most important issues in FA. In practice the
218 distribution of hydroclimatic series is not known. Using the fitted probability distribution, it is
219 possible to predict the probability of exceedance for a specified magnitude, i.e. quantile, or the
220 magnitude associated with a specific exceedance probability. To estimate the parameters
221 associated to the appropriate probability distribution, popular techniques are used in hydrology,
222 including the methods of Maximum Likelihood (ML)[e.g. 17, 46], Moments (MM) and
223 Probability Weighted Moments (PWM) [e.g. 13, 32]. The latter is equivalent to the L-moment
224 method which is widely used in hydrological FA[29].

225 The choice of the adequate distribution is determined on the basis of numerous classical and
226 recent statistical tools, including graphical representations [34, 46] and goodness-of-fit tests
227 such as the tests of Pearson (Chi-squared, χ^2), Kolmogorov-Smirnov (KS), Cramer-von
228 Mises and the normality specific Shapiro-Wilk (SW) test. Due to the importance of the
229 distribution impact in FA, these tools should be exploited. This point is widely studied in the
230 literature [8, 20, 22, 28, 31, 38 and 47].

231 Nonetheless, the decision procedures mentioned above are not perfectly suited for extreme
232 value distributions, because they are not sensitive enough to deviations in the tails. Several
233 transformations have been proposed to overcome the limitations of the aforementioned tests
234 [36, 39, 41]. In our application, where we focus on the upper tail of the distribution, we perform

235 the Anderson-Darling k-sample test ($k=2$) implemented in the `adk` package of the statistical
236 software R. This procedure is used to test the null hypothesis that k samples come from one
237 common continuous distribution. In our case, the first sample of size 42 is the considered POT
238 series and the second one consists in values generated from the GPD model. For more details
239 on this test, we refer to [53].

240 The probability distributions that are appropriate for hydrology data are those with heavy tails.
241 A number of them are listed, e.g. in [37, 49, 52]. In order to select the appropriate distribution
242 among those which passed the goodness-of-fit tests, one or more criteria are required. To this
243 end, one can consider the Akaike and Bayesian information criterion (AIC, BIC) respectively
244 proposed by Akaike [2] and Schwartz [54]. They are given by:

$$245 \quad AIC = -2 \ln L + 2k, \quad (6)$$

$$246 \quad BIC = -2 \ln L + 2k \ln m \quad (7)$$

247 where L is the likelihood function, k the number of parameters and m the sample size. The best
248 fit is the one associated with the smallest criterion AIC or BIC values [20, 28, 49].

249 *3.5. Quantile Estimation*

250 Once the appropriate distribution selected, the quantiles and return periods can be evaluated.
251 The quantile estimation for various recurrence intervals is the main goal in hydrological practice.
252 The notion of return period for hydrological extreme events is commonly used in FA, where
253 the objective is to obtain reliable estimates of the quantiles corresponding to given return
254 periods of scientific relevance or government standard requirements[49]. In the FA context the
255 uncertainty decreases with the sample size whereas it increases with the return period when
256 estimating quantiles.

257 In many environmental applications the sample size is rarely sufficient to enable good extreme
258 quantiles estimations. Usually, a quantile of return period T can be reliably estimated from a
259 data record of length n if $T < n$. However, in many cases, this condition is rarely satisfied –since
260 typically $n < 50$ for hydrological applications based on annual data[31].

261 3. Results and discussion

262 The application of the presented methodology in section 3 to the data described in section 2
263 leads to the following results, obtained by means of the packages stats, evir and POT of the
264 statistical software R [33] and also by using the HYFRAN-PLUS software[21].

265 4.1. Exploratory Analysis and Outlier Detection

266 From Figure 2, it appears that the whole daily data series vary from a minimum value of $0 \text{ m}^3 / \text{s}$
267 corresponding to many dry days, to a maximum value of $78.57 \text{ m}^3 / \text{s}$ recorded on September
268 21st, 1989. The average flow of $0.39 \text{ m}^3 / \text{s}$ is a relatively low in comparison with other tributary
269 wadis of Chott Melghir like El Hai wadi and Djamorrah wadi [42]. The standard-deviation of
270 $2.48 \text{ m}^3 / \text{s}$ yields a coefficient of variation equal to 6.39. The box-plot in Figure 3 clearly
271 shows the existence of extreme values. Indeed, the median ($0.10 \text{ m}^3 / \text{s}$) is close to both 25th
272 and 75th percentiles ($0.04 \text{ m}^3 / \text{s}$ and $0.20 \text{ m}^3 / \text{s}$). In addition to this graphical consideration, the
273 values of skewness and kurtosis ($20.51 \text{ m}^3 / \text{s}$ and $498.59 \text{ m}^3 / \text{s}$ respectively) eliminate the
274 Gaussian model. In particular the very large value of the kurtosis indicates longer and fatter
275 distribution tails, urging us to focus on heavy-tailed models

276 From **Erreur ! Source du renvoi introuvable.**, we observe high inter-annual and the short
277 sample size (resulting from selection AM) which leads to selecting low discharges during the
278 driest years whereas some interesting discharges were not selected during the years where

279 several floods have occurred. This explains the non-relevance of the AM approach for Abiod
280 wadi data analysis and suggests that the POT approach would be more appropriate, and would
281 lead to a more homogeneous sample of extreme discharges. This method starts with the
282 selection of a convenient threshold, then the consideration of the observations that exceed this
283 threshold.

284 In order to detect outliers, the quantities x_H and x_L are found to 508.31 and 0.08 respectively.
285 Since there is no value greater than x_H and nor less than x_L , we conclude that, at the significant
286 level of 10 %, no outlier exist among the excesses. Since it is difficult to use the outlier detection
287 test with the analysis of extremes and due to the lack of regional weather data, the significance
288 level to 10% is considered.

289 *4.1.1.Threshold Selection*

290 In this study, we adopt one of the available graphical tools, namely the TC-plot. From Figure
291 4we can choose a threshold value $u = 5.6 m^3 / s$, which results in an excess series of size
292 58.However, as recommended by many authors [9, 40, 56], this data set must be reduced in
293 order to avoid the effects of dependence. We eliminated the peaks being obviously part of the
294 same flood, and in order to keep the character of flood seasonality, we retain three peaks per
295 year over the recorded period. Thus, the length of the data series becomes 42. Figure 5shows
296 the distribution of these excesses and Table 1summarizes their elementary statistics.

297 The positive skewness coefficient $C_s=1.62$ reveals that the data is right skewed relative to the
298 mean excess, as shown in **Erreur ! Source du renvoi introuvable.a**. In Figure 5a, the data are
299 arranged by classes, of length $10 m^3/s$ each, with the associated frequencies. It can be seen that
300 some values are more frequent than others and that the majority of excesses have a low value
301 varying between 0 and $10 m^3/s$. **Erreur ! Source du renvoi introuvable.b**, where the data are

302 arranged according to the months of appearance, shows that the peaks generally occur in the
303 fall season.

304 *4.2. Testing the Basic FA Assumptions*

305 The results of the required hypothesis testing on the considered data are given in Table 2.
306 Applying Wilcoxon, Kendall and Walf-Wolfowitz tests respectively, we conclude that the
307 homogeneity, stationarity and independence of the excesses are accepted at any of standard
308 significance levels (1%, 5% and 10%). Note that for the homogeneity test, we split the data in
309 two sub-series 1972-1981 and 1982-1994 (any other subdivision led to the same conclusion).
310 The homogeneity can also be noted in *Erreur ! Source du renvoi introuvable.a* where there is only one
311 mode (the highest frequency).

312 *4.3. Model Fitting*

313 To fit a statistical distribution, we consider three commonly used estimation methods of the
314 GPD parameters (ML, MM, and PWM). Then we perform the Anderson-Darling test to check
315 the goodness-of-fit of the model. The results are summarized in Table 3. In view of the large P-
316 values, we deduce that the GPD can be accepted as an appropriate model for the excess at any
317 standard significance level (for instance 5%).

318 To discriminate between the obtained models, we use the AIC and BIC criteria. The last two
319 columns of Table 3 as well as Figure 6b favor the GPD of the ML fitting method. We illustrate
320 the goodness of fit of the excesses to this model in **Erreur ! Source du renvoi introuvable.a**.
321 Furthermore, this ML-based will be used for quantile estimation in the following section.

322 Note that the ML and PWM results are very similar whereas those of the MM results are slightly
323 different but remain in the same range.

324 4.4. Quantile Estimation

325 The estimation of extreme quantiles for different return periods should take into consideration
326 the record period and the right tail of the distribution. The formally gauged record represents a
327 relatively small sample of a much larger population of flood events. Thus, the extrapolation for
328 long return periods is less accurate. In the M'chouneche station only the following return
329 periods were considered for the estimation of quantiles: 2, 5, 10, 20 and 50 years as presented
330 in Table 4. The return period of the strongest streamflow in the 1972-1994 period, equal to
331 78.57 m³/s, is estimated by means of Pareto's fitted model to be 30.62 years.

332 The confidence interval is a way to assess the uncertainty in the estimation of the distribution
333 parameters and quantiles. For the GPD, the confidence bounds are obtained through asymptotic
334 results [31]. In the present case-study, one can see from **Erreur ! Source du renvoi**
335 **introuvable.c** that the GPD agrees with the observations for return levels less than 30 but not
336 beyond even though they are all included in the confidence interval. This is probably due to the
337 small number of peaks over the chosen threshold. Therefore, it is important to consider this
338 distribution with care with return periods greater than 30 years. This point indicates the issue
339 of the quantity of the required data in this station for better estimation of high return periods.

340 4. Conclusions

341 The study of the Algerian wadis floods remains a quasi-unknown field as only some
342 very specific indications are given in the Algerian hydrological directories. Floods are one of
343 the basic features of a stream regime. The present study, which is the first one carried out in
344 southern east of Algeria with new data series, in the context of FA. Mean daily discharges data
345 recorded at the gauging station of M'chouneche in Abiod wadi, near Biskra, are available and
346 considered in the present study. Due to the high inter-annual variability of the data as well as
347 to the relatively short record length, the AM approach is not adapted to this analysis. Hence, in

348 this paper, we considered a more appropriate procedure, namely the POT method.

349 The purpose of this work is to provide a suitable model for the excesses over a chosen threshold.

350 This allows to estimate extreme flood events of given return periods. A complete FA was

351 applied including appropriate tools, commonly used in hydrology. The issue of threshold

352 selection was dealt by the means of a graphical tool. Several fitting methods have led to

353 different GPD models and according to the results, the ML-based distribution was adopted.

354 Because of the short record length, only return periods of 2, 5, 10, 20 and 50 years were

355 considered. It was found that most of extracted data corresponded to frequent events. In the

356 present case study, the GPD distribution provided good estimates of return periods less than 30

357 years but for higher values, the estimation is not acceptable and it is associated with high

358 uncertainty (large confidence interval).

359 As a conclusion, we should emphasize that, in addition to the quality of data and sample size,

360 the right choice of a GPD model heavily depends on the threshold. To improve the flood FA at

361 this site, future studies should focus on the importance of data monitoring. However, this

362 conclusion even it is not new in FA, it is important for the studied area where this is the first

363 time to be studied. It emphasizes and confirms the importance of this issue, especially for local

364 government and decision makers.

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519 **Table 1. Statistics summary of excess data set.**

520

Size	42 observations
Minimum	0.02 m ³ /s
Qu ₁ (25 th percentile)	3.36m ³ /s
Median	7.83m ³ /s
Average	15.72m ³ /s
Qu ₂ (75 th percentile)	19.92m ³ /s
Sd	19.70 m ³ /s
Maximum	72.97m ³ /s
Cs	1.62
Ck	4.48

521

522 **Table 2. Stationarity, independence and homogeneity tests results.**

Tests	Statistic value	p-value
Stationarity (Kendall)	0.48	0.63
Independence (Wald-Wolfowitz)	0.94	0.35
Homogeneity(Wilcoxon)	0.79	0.43

523

524

525 **Table 3. GPD parameter estimation, Anderson-Darling goodness-of-fit test and**
 526 **information criterion results.**

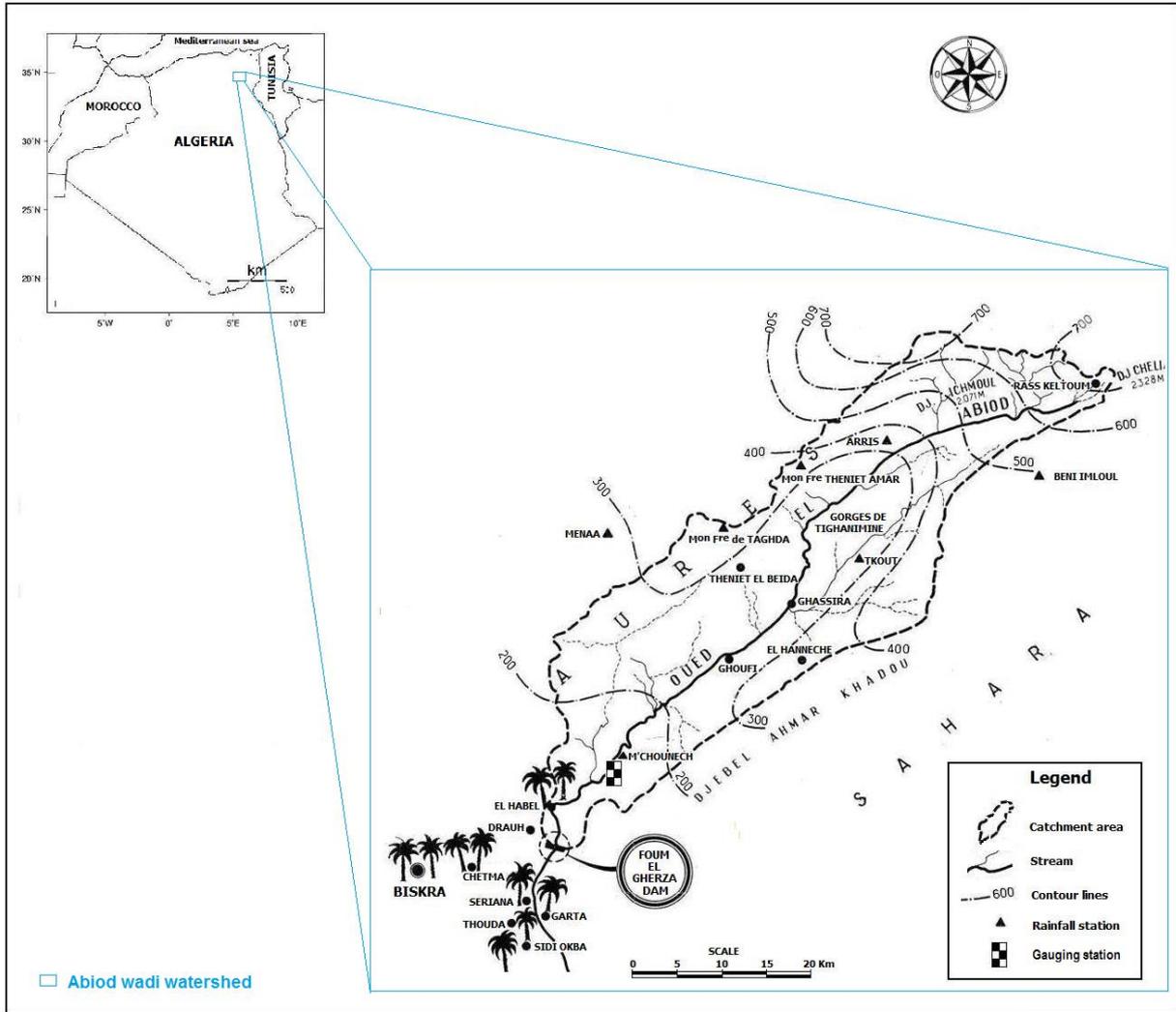
Estimation method	Scale	Shape	Statistic value (Anderson-Darling)	p-value	AIC	BIC
ML	10.19	0.39	-0.55	0.49	315.68	326.63
MM	12.86	0.18	-0.83	0.58	316.61	327.56
PWM	10.10	0.36	-0.86	0.59	315.72	326.68

527

528 **Table 4. Estimated quantiles of excess flows from the ML-based GPD.**

Return period (years)	Estimated quantile (m3/s)
2	8.11
5	22.80
10	37.96
20	57.82
50	93.82

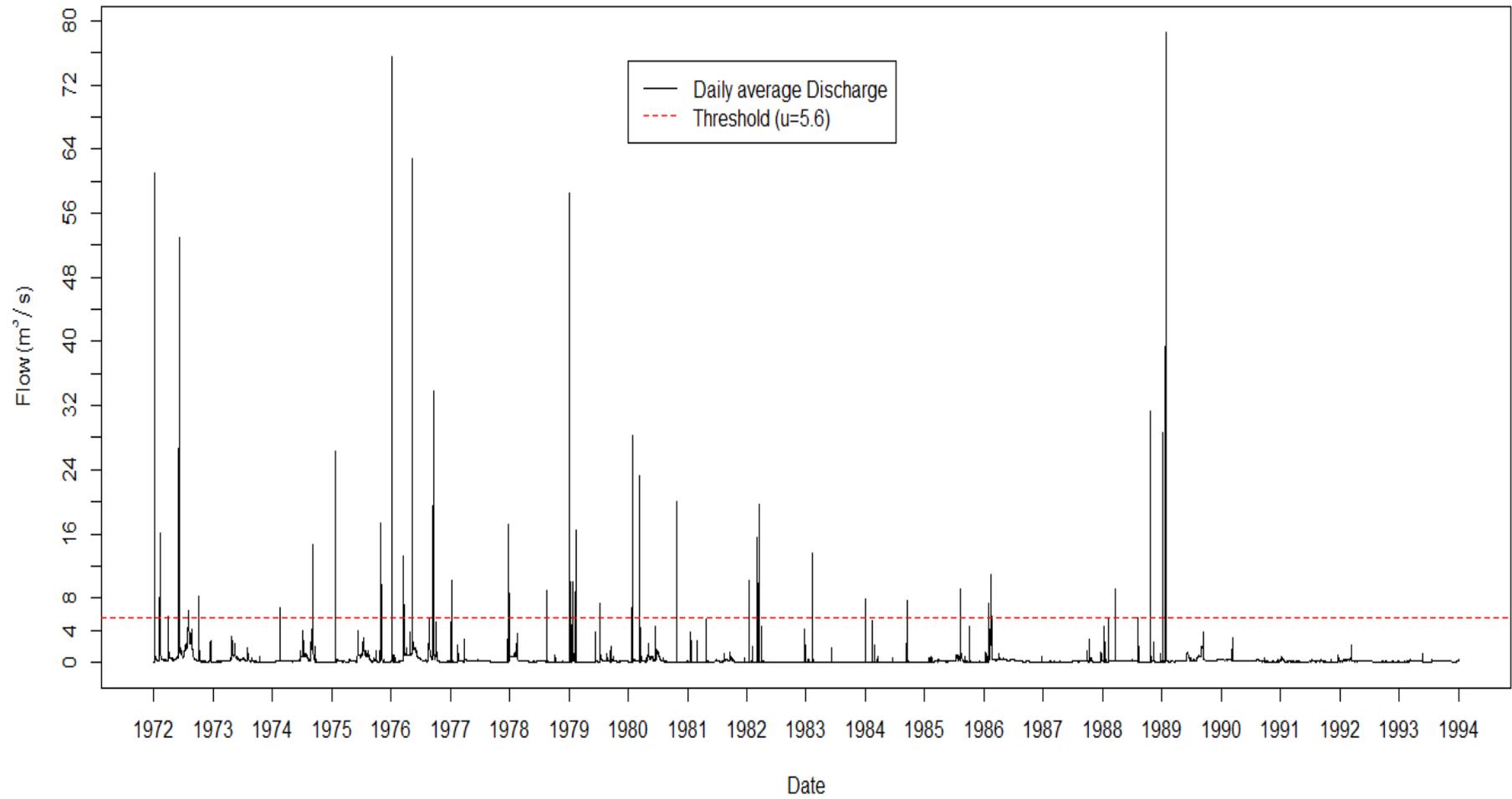
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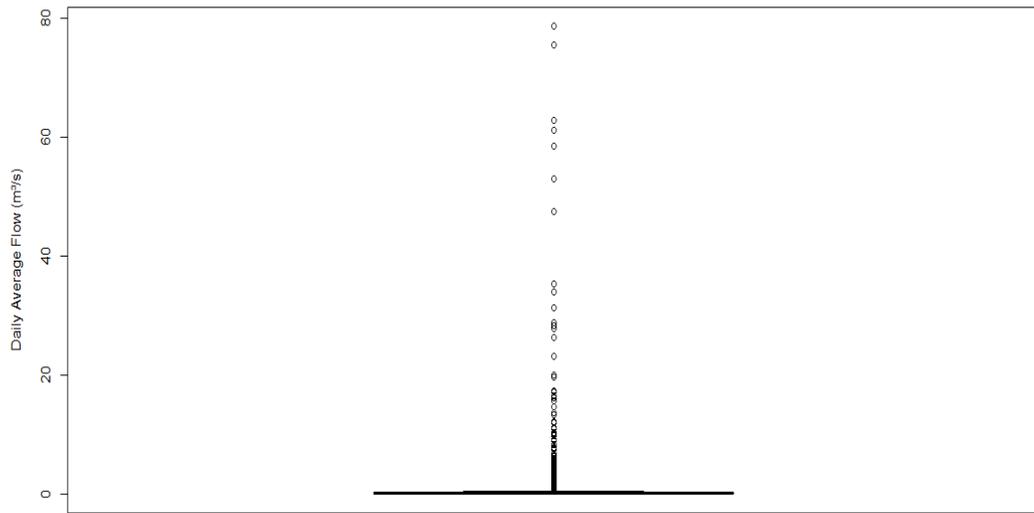
Figure 1. Geographical location of the Abiod wadi watershed



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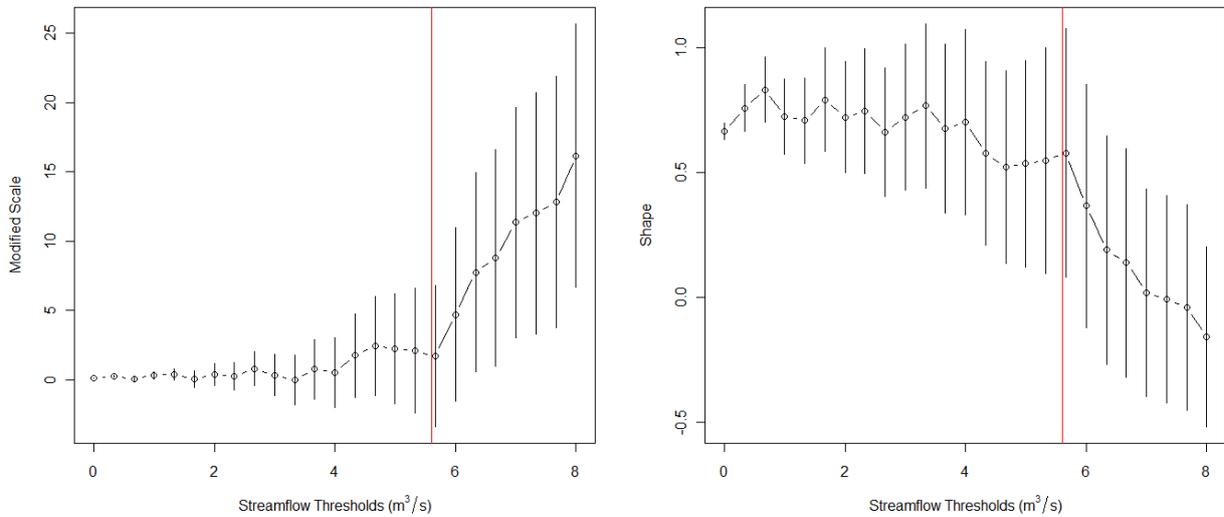
Figure 2. Time series plot of the daily average discharge at M'chouneche station covering the period 01/09/1972-31/08/1994.



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Figure 3.Box plot of daily average discharge at M'chouneche station.



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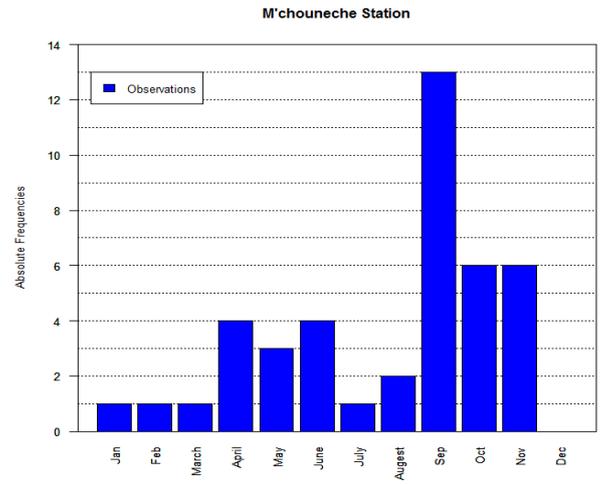
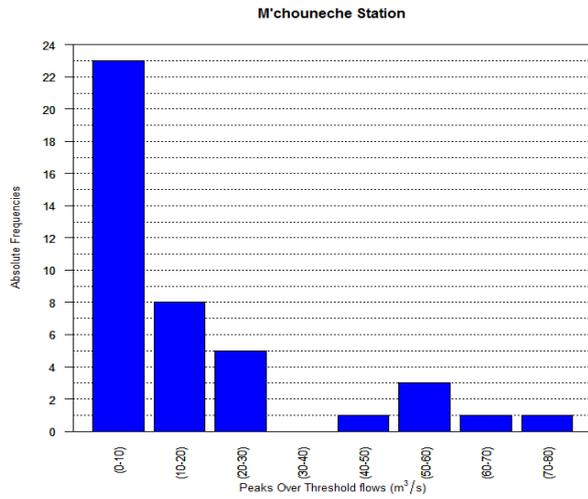
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Figure 4.Graphical results of threshold selection applied for daily average discharge of Abiod wadi at M'chouneche station (tc-plot), vertical line corresponding to the threshold.

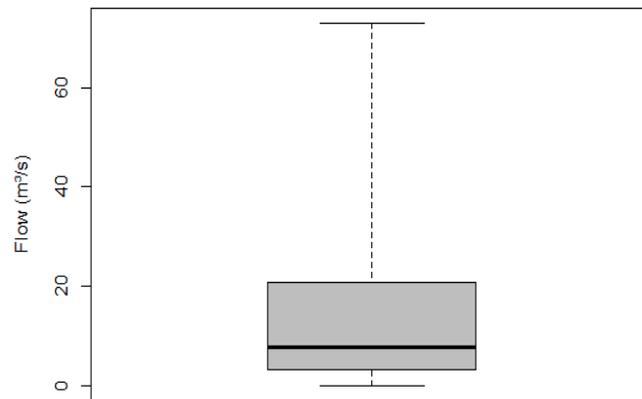


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542

a)

b)



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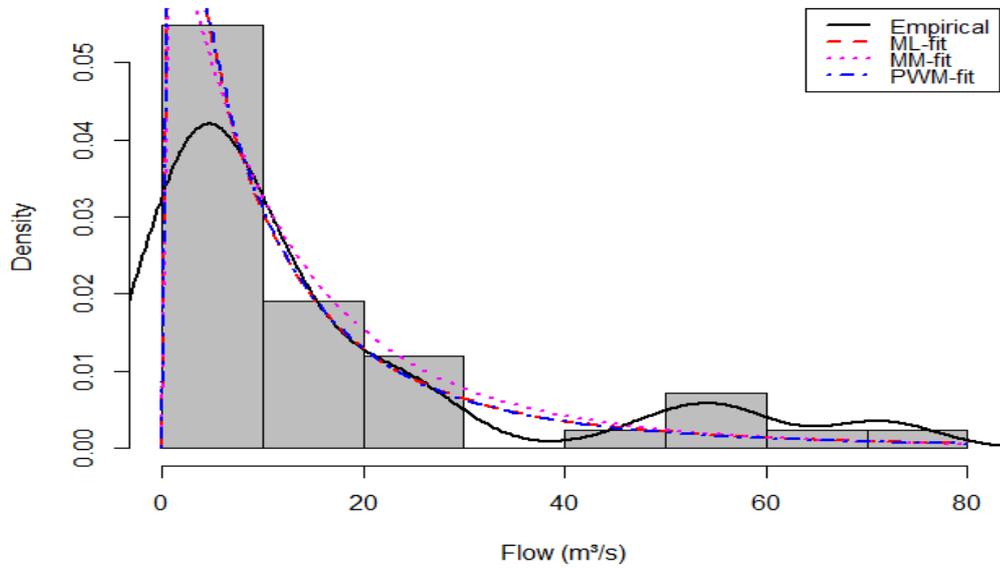
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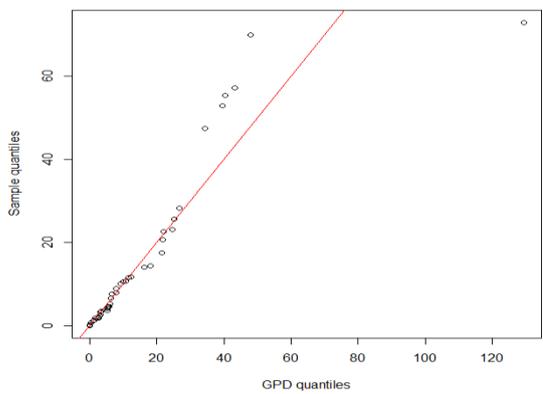
Figure 5. Distribution of excess series at M'chouneche station a) Histogram by flow classes b) Histogram by month c) boxplot.



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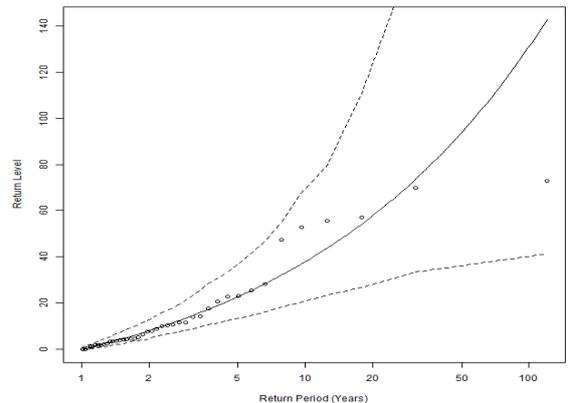
a)



551

552

b)



553

554

555

c)

Figure 6. Best fitted distributions of excess flows at M'chouneche station a) distributions b) qq plot of ML-based GPD c) Return level plot (95% confidence interval)