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Review

Regional approach for the estimation of extreme daily precipitation on North-east area of Algeria

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Information on precipitation values and their frequencies is needed in various projects related to water. In this study, the regional frequency analysis based on L-moments was used to estimate the annual maximum daily precipitation quantiles at any site in an area located in the north east of Algeria. The investigated area was divided into three regions statistically homogeneous in terms of L-moments ratios. Among the different tested distributions, (i) the Generalized Extreme Value (GEV) distribution has been identified as the most appropriate regional distribution for modeling precipitation in the northern region (region 1) characterized by a Mediterranean climate and (ii) the generalized lognormal distribution (LN3) for region 2 of southern part subject to semi-arid climate. Growth curves, derived from the regional distributions, were established for each homogeneous region. The growth curves shapes difference reflects the difference between the three homogeneous regions precipitation patterns. The regional model efficiency was put into evidence via a comparison of the specified return period's quintiles estimated from the regional and at-site frequency. The root mean square error values (RMSE) were found to be below 6% for a return period of 10 years and 12% for a return period of 100 years.

Key words: Maximal annual daily precipitation, L-moments, regional frequency analysis, GEV, LN3 distributions, set generation.

INTRODUCTION

The estimation of precipitation associated with extreme events is a topic of growing interest in all areas related to water. The knowledge of some return period precipitation quantiles is necessary for the design of hydraulic structures such as flood protections and storm sewer systems. Design of such structures often requires a realistic estimation of extreme precipitation in sites where no or few rainfall data are available. The estimation of precipitation in sites with no data by hydrologists and meteorologists is often made by the use of spatial interpolation methods or methods of regional frequency analysis.

The spatial interpolation methods estimate a related precipitation statistics value or the precipitation amount at a given frequency in a geographic point. These methods of interpolation use the correlation or a multiple regression functions requiring many explanatory parameters for the variable to be studied. Goovaets (2000), Touaïbia et al. (2006) applied different methods of spatial interpolation based on the related parameters of the study areas relief to map the precipitation distribution.

In contrast to the spatial interpolation methods, the regional frequency analysis estimate the quantiles associated with different return periods at any site within an area by combining the regional and at site information. The frequency analysis methods were initially developed for flood estimation by Dalrymple in 1960. Since then these methods were continuously developed. GREHYS (1996a) and Ouarda et al. (1999, 2008) in their studies on

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the regionalization of flood presented and compared different methods.

The flood frequency analysis was applied to regionalization of precipitation which was then the basis for much research work. Alila (1999) developed a hierarchical regional frequency model for precipitation of short duration in Canada. Djerboua (2001) and Mora et al. (2005) focused on the regional estimation of daily precipitation in France. Nguyen and al. (2002) proposed two alternative methods for estimating extreme precipitation of various durations. Kysely and Picek (2007) used a method based on L-moments to estimate regional precipitation. Regional frequency analysis based on the index variable method and L-moments was utilized by Norbiato et al. (2007) to analyse short duration annual maximum precipitation in Italia. Gellens (2002) combined the regional approach and data extension procedure for estimation of extreme precipitation in Belgium. Gaal et al. (2008) applied region-of-influence method to a frequency analysis of heavy precipitation in Slovakia.

In his literature review on regionalization of precipitation, St-Hilaire (2003) pointed out that most regional analysis methods follow the steps of the determination of homogeneous hydrological regions, the identification of regional distribution and the estimation of parameters and quantiles of this distribution.

In this study, the regional frequency analysis method based on L-moments was used to estimate the quantiles of different return periods of maximum annual daily precipitation at any site in the study area situated to North East of Algeria. After the data description in “study area and data” and the method used in “method of regionalization” part of this work, the results of application of the three steps of regional frequency analysis were presented and discussed; these are the formation of homogeneous regions, the identification of regional frequency distribution and the estimation of parameters and quantiles of the fitted distribution. A conclusion is finally made.

Study area and data

The study area is located in northeast Algeria. It covers the watersheds of two major wadis Seybouse and Medjerda, (Figure 1). 50 annual maximum daily precipitation recording stations were chosen for the purpose of the study. Most observations concern the period 1970 to 2007. The mean sample size is 36 years. Despite that the mean annual maximum daily precipitation varies considerably from 26.1 to 61 mm, the coefficients of variation remain relatively constant. Their variation is only around a mean value of 0.407 with a standard deviation equal to 0.07. Unlike the coefficients of variation, the coefficients of skewness exhibit spatial variability; their mean and standard deviation are respectively equal to 1.02 and 0.47.

METHOD OF REGIONALIZATION

Definition of homogeneous regions and homogeneity test

Constitution of station groups

The first stage of the regional approach is the determination of homogeneous regions defined as hydrologically homogeneous group of stations. The identification of homogeneous groups is made by the specification of variables characterizing this homogeneity.

Homogeneous regions can be obtained by the variability geographical analysis of the data’s coefficients of variation or skewness, which have to be constant or slightly variable for a homogeneous region (Versiani et al., 1999). In the present study, and in compliance with a common practice (Smithers and Schulze, 2001; Kjelden et al., 2002) a cluster analysis of site characteristics is used to form groups of stations and the L-moments ratios are specified as statistics characterizing the homogeneity of defined groups. Before the description of the validation process of the regional homogeneity of station groups, a brief review of L-moments theory is made.

L-moments

Some problems in the interpretation of the information held by higher-order moments when using the statistic laws fitting methods based on traditional moments may rise. The parameters fitted by the method of moments can be different from those of the distribution from which the sample is obtained and especially when the size of this one is small. To avoid this, Hosking (1990) proposed the use of L-moments, which are analogous to traditional moments. Their estimation can be made from linear ordered data combinations.

For an ordered sample. $x_1, x_2, x_3, \ldots, x_n$ where $x_{1:n} < x_{2:n} < \ldots < x_{n:n}$ the probability weighted moments (PWM) are estimated by:

$$\begin{aligned}\beta_0 &= n^{-1}\sum_{j=1}^{n} x_{j:n}\\ \beta_1 &= n^{-1}\sum_{j=2}^{n} \frac{j-1}{n-1} x_{j:n}\\ \beta_2 &= n^{-1}\sum_{j=3}^{n} \frac{(j-1)(j-2)}{(n-1)(n-2)} x_{j:n}\\ \beta_3 &= n^{-1}\sum_{j=4}^{n} \frac{(j-1)(j-2)(j-3)}{(n-1)(n-2)(n-3)} x_{j:n}\end{aligned} \quad (1)$$

Therefore, for example we can estimate L-moments using the following *PWM:*

$$\begin{aligned}l_1 &= \beta_0\\ l_2 &= 2\beta_1 - \beta_0\\ l_3 &= 6\beta_2 - 6\beta + \beta_0\\ l_4 &= 20\beta_3 - 30\beta_2 + 12\beta_1 - \beta_0\end{aligned} \quad (2)$$

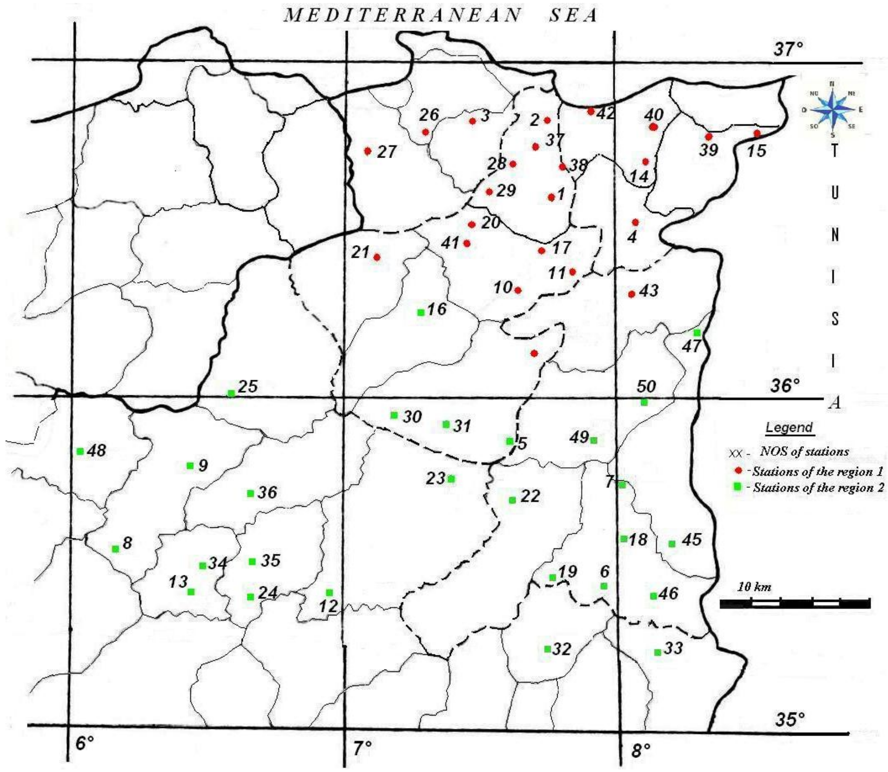

Figure 1. Study area and location of stations. The Seybouse and Medjerda large wadis basins are delimited by a broken line.

The first L-moment l_1 is equal to the mean of the distribution and l_2 is a scale parameter (L-standard deviation). In addition, the following L-moments ratios were introduced:

L-coefficient of variation, *L-Cv*, $(t) = l_2 / l_1$ (3)

L-skewness, *L-Cs,* $(t_3) = l_3 / l_2$ (4)

L-kurtosis, *L-Ck,* $(t_4) = l_4 / l_2$ (5)

Test of homogeneity

To confirm the homogeneity of a region (that is to say a group of stations) in terms of the L-moment ratios, the Hosking and Wallis (1997) statistic test is used in which the representative parameters of a region are the weighted averages L-moment statistics. Therefore, for a region of *N* stations having each n_i length recording, the regional L-moment ratios and L-moments are calculated as follows:

$$\bar{t}_r = \frac{\sum_{i=1}^{N} n_i t_r^{(i)}}{\sum_{i=1}^{N} n_i} \qquad r \geq 3 \tag{6}$$

$$\bar{l}_r = \frac{\sum_{i=1}^{N} n_i l_r^{(i)}}{\sum_{i=1}^{N} n_i} \qquad r \geq 1 \tag{7}$$

where $t_r^{(i)}$ and $l_r^{(i)}$ are respectively the L-moments ratios and the L- moments of order r at station *i*.

The L-coefficient of variation (*L-Cv)* of a sample is defined by: $t = l_2 / l_1$

The Monte Carlo test simulation is used in order to test the homogeneity of a region. Many of the regional data are generated from the four-parameter Kappa distribution. Kappa distribution is adjusted by using the regional weighted average L-moments. Each simulation must reflect the configuration of the considered regional database. More precisely during a simulation, the number of sites and the number of observations at each site must be reproduced. For each generated region, the three measures of variability between sites of the L-moments ratios are calculated as follows:

The weighted variance of *L-Cv*:

$$V_1 = \frac{\sum_{i=1}^{N} n_i \left(t^{(i)} - \bar{t}\right)^2}{\sum_{i=1}^{N} n_i} \tag{8}$$

The weighted average distance from the site to the region weighted mean on the *L-CV* versus L-skewness space:

$$V_2 = \frac{\sum_{i=1}^{N} n_i \sqrt{\left(t^{(i)} - \bar{t}\right)^2 + \left(t_3^{(i)} - \bar{t}_3\right)^2}}{\sum_{i=1}^{N} n_i} \quad (9)$$

The weighted average distance from the site to the region weighted mean on the L- skewness versus L-kurtosis space:

$$V_3 = \frac{\sum_{i=1}^{N} n_i \sqrt{\left(t_3^{(i)} - \overline{t_3}\right)^2 + \left(t_4^{(i)} - \overline{t_4}\right)^2}}{\sum_{i=1}^{N} n_i} \quad (10)$$

where $t^{(i)}$, $t_3^{(i)}$ and $t_4^{(i)}$ denote respectively the *L-Cv, L-Cs* and *L-Ck* at site *i*; $\bar{t}$, $\overline{t_3}$ and $\overline{t_4}$ denote the regional *L-Cv, L-Cs* and *L- Ck* calculated according to Equation (6); *N* is the number of sites. If V denotes any of the three values V_1, V_2 and V_3 , the criterion of homogeneity of a region is calculated as follows:

$$H = \frac{V_{obs} - \mu_v}{\sigma_v} \quad (11)$$

where V_{obs} is the *V* observed value, μ_v and σ_v are respectively the mean and standard deviation of *V* obtained by simulations. The variable *H* enables to measure the dispersion of observations relatively to those of the simulations. According to Hosking and Wallis (1997), a region is acceptably homogeneous if *H* <1, probably heterogeneous if $1 \leq H < 2$ and definitely heterogeneous if $H \geq 2$.

Identification of regional distribution

Among the different frequency distributions, the Gumbel distribution is the most often used in Algeria in the frequency analysis of extreme precipitation events in a single site. This distribution was used by Mebarki (2005) in the frequency analysis of annual maximum daily rainfall in eastern Algeria.

This two parameters distribution is also widely used in different climatic regions. The asymptotic behavior of the Gumbel distribution is however challenged by Koutsoyiannis (2004), confirming that its effect is to underestimate the precipitation values of high frequencies compared to the distribution GEV (EV2) (Generalised Extreme Value, type 2). Alila (1999) raised some concern on the use of Gumbel distribution in a regional context. In his study on the regionalization of short duration precipitation in Canada, different distributions have been adjusted and the GEV distribution was identified as the most appropriate regional distribution. This latter is the most widely used for both the precipitation regional frequency analysis and flood. Overeem et al. (2007) have used it for the regionalization of short duration precipitation in whole Holland. Djerboua (2001), Versiani et al. (1999) and Cannarozzo et al. (1995) have chosen the TCEV distribution (Two Component Extreme Value) as the regional statistical model of annual maximum daily precipitations. To determine growth curves regional precipitations of short duration Sveinsson et al. (2002) used a regional approach based on the flood frequency index method taking into account the different distributions: Lognormal distribution with three parameters (LN3), GEV, lognormal (LN) and Pearson type 3 (P3).

In the present study, the hypothesis of fitting the GEV, LN3, P3 and GLO (Generalized Logistic) distributions with the series of annual maximum daily precipitation of the study area is made. The suitability of fitting each of these three parameters distributions is evaluated by the difference between the theoretical L-kurtosis of the fitted distribution and the regional L- kurtosis. The significance of this difference is assessed through the Z statistic (Hosking and Wallis, 1997):

$$Z^{DIST} = \frac{\overline{t_4} - \tau_4^{DIST}}{\sigma_{\overline{t_4}}} \quad (12)$$

where $\overline{t_4}$ is the observed regional weighted average L- kurtosis, τ_4^{DIST} is the theoretical L- kurtosis of the distribution (DIST) estimated from the observed regional L- skewness. The $\sigma_{\overline{t_4}}$ is the standard deviation of $\overline{t_4}$ obtained by simulations of a homogeneous region with Kappa distribution. The Z statistic is based on asymptotic normality and the fit is satisfied at the 90% confidence level if $|Z| \leq 1.64$.

Estimation of parameters and quantiles of the regional distribution

The parameters of the regional distribution are estimated from the first three regional L-moments. The regional growth curve will be established on the basis of the regional distribution parameters by applying the mean as a scaling factor (index storm). In this approach, the regional L-skewness and L- coefficient of variation are assumed to be constant. Therefore, to estimate the precipitation associated with different return periods at a given site of a homogeneous region, the values of the growth factor corresponding to the same return period will be multiplied by its mean daily maximum precipitation.

RESULTS AND DISCUSSION

Before the application of frequency analysis, data of each station were checked in terms of a discordance measure based on L-moments ratios (Hosking and Wallis, 1997). The values of discordance measure of the 50 stations range from 0.27 to 2.14. They are both less than the critical value which is equal to 3. Consequently, the data of all stations can be used in regional frequency analysis.

The next step was the definition of homogeneous regions. The cluster analysis of the station characteristics (longitude, latitude, altitude, mean annual precipitation and mean annual number of rainy days) was used as auxiliary tool for the formation of stations groups. K clusters (k = 2, ... 4), obtained by the application of two aggregation methods (method of "average link" and Ward's method), have been studying. To better interpret the results of clustering and use in the formation of homogeneous regions the Silhouettes method (Rousseeuw, 1987) was used. Based on this method, the statistical homogeneity of ten different partitioning of stations has been tested in terms of Hosking-Wallis test. Finally, the partitioning of the stations is led to the formation of two homogeneous regions (Figure 1). It is observed from Figure 1 that there is a spatial homogeneity in the group of stations. Stations of the region 1 are located in the northern part of the study area characterized by a Mediterranean climate. The mean annual precipitation of this region varies from 442 to 804 mm. Stations of the region 2 are located in the southern part of the study area subject to a semiarid climate. The mean annual precipitation of this latter varies from 233 to 512 mm.

The statistics of the two regions are shown in Table 1. To assess the homogeneity degree of regions, 500 data regions were generated using the Kappa distribution. According to the obtained values of the heterogeneity measure H (Table 2), regions 1 and 2 are homogeneous in terms of *L-Cv, L-Cs,* and *Ck.*

The two regions are homogeneous; therefore to identify the regional distribution of each region among the GEV, P3, LN3 and GLO distributions, the Z^{DIST} statistics for these was calculated by distributions carrying out 500 simulations using the Kappa distribution. The values obtained for these latter and the theoretical L-kurtosis values of each fitted distribution are given in Table 3. According to Z-statistic values, LN3 and GEV distributions are plausible adjustment of the sample region 1 and region 2. To make the final choice of regional distribution the L-moment ratio diagram was used. The samples L-moments ratios (t3, t4) and their weighted regional averages were reported in the diagram (Figure 2). Points defined by the regional mean values of L-Cs and L-Ck (Figure 2) are close to the GEV distribution for region 1 and LN3 for region 2. Thus, based on the L-moment ratio diagram and also on the values of Z -statistic, the GEV and LN3 distributions are identified as the most robust distributions for the region 1 and 2, respectively.

The quantile function of the GEV distribution is as follows:

$$x(F) = \xi + \frac{\alpha}{k}\left\{1 - \left[-\ln(F(x))\right]^k\right\} \text{ pour } k \neq 0 \tag{13}$$

The cumulative distribution function of the LN3 is given as follows:

$$F(x) = \frac{1}{\sigma\sqrt{2\pi}} \int_0^u \frac{1}{u} e^{\frac{\ln^2(u)}{2\sigma^2}} du \tag{14}$$

Table 1. Region statistics.

Region	*N*	$\bar{l}_1$	$\bar{l}_2$	$\bar{t}$	$\bar{t}_3$	$\bar{t}_4$
Region 1	23	51.61	10.98	0.211	0.174	0.154
Region 2	27	36.48	8.29	0.227	0.204	0.151

N: number of stations; $\bar{l}_1$ and $\bar{l}_2$: the regional mean and standard deviation (expressed in mm).

Table 2. Results of homogeneity test for the different regions.

Region	H_1	H_2	H_3
Region 1	0.79	-0.80	-0.91
Region 2	0.93	-0.32	-0.78

Table 3. Theoretical L-kurtosis and Z-statistic of different distributions.

Distribution	Region 1		Region 2	
	τ_4^{DIST}	Z	τ_4^{DIST}	Z
GEV	0.152	-0.24	0.175	0.87
LN3	0.146	-0.57	0.163	0.32
P3	0.126	-1.87	0.128	-1,69
GLO	0.192	2.29	0.209	2.79

where $u = \frac{x - \xi}{\alpha}$ and ξ, α and σ *(k)* are the location, scale and shape parameters respectively. For a sample, these parameters are defined from L-moments by the following equations:

$$\xi = l_1 - \frac{\alpha}{\sigma}\left(1 - e^{\sigma^2/2}\right) \tag{15}$$

$$\alpha = \frac{l_2 \sigma \exp(-\sigma^2/2)}{erf(\sigma/2)} \tag{16}$$

$$\sigma = -t_3 \frac{A_0 + A_1 t_3^2 + A_2 t_3^4 + A_3 t_3^6}{1 + B_1 t_3^2 + B_2 t_3^4 + B_3 t_3^6} \tag{17}$$

where *erf* is the error function; $A_0, \ldots, A_3$ and B_1, B_2, B_3 are the constants of approximation.

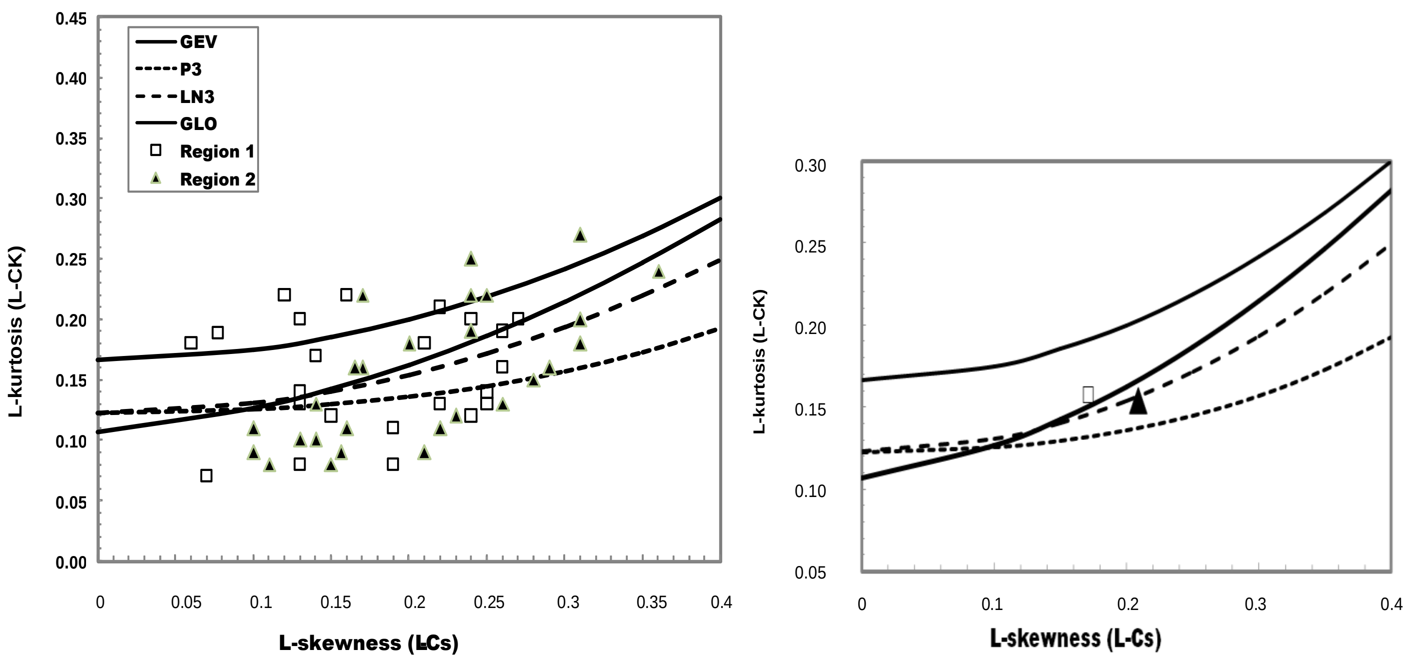

Figure 2. L-moment ratio diagram. L-moment ratio values ((t_4 / t_3) of stations (regional means) are shown on the left (right) figure.

Table 4. Regional parameters of GEV and LN3 distributions.

Region		ξ	α	σ **(*k*)**
Région 1	GEV	0.826	0.302	-0.010
Région 2	LN3	0.918	0.373	-0.422

The regional parameters of these distributions of all two homogeneous regions (Table 4) were estimated using the regional L-moments as outlined in "estimation of parameters and quantiles of the regional distribution" part of this work. Regional growth curves, derived from the regional distributions, were plotted for specified return periods T (Figure 3). These growth curves show the variation of growth factor *q (F)* versus the not exceeded probability *F* or versus the return period T, $(T = 1/1 - F)$. It is observed from Figure 3, that the values of growth factor of homogeneous region 2 are stronger than those of homogeneous region 1. This can be probably explained by the regional climatic particularity. The L- coefficients of skewness ($\bar{t}_3$) of this region subject to a semi-arid climate are higher than the one of region1 subject to a Mediterranean climate.

To evaluate the accuracy of estimates, the growth factor of each homogeneous region a re-sampling procedure called jack-knife was applied. This excludes data from a station among all N stations in a region and estimates after that the regional parameters of the LN3 and GEV distributions and also the growth factors from the data of the region which consists of N-1 remaining stations. For a homogeneous region, this process is repeated as many times as there are stations.
(19)

To evaluate the performance of growth factor estimation for each homogeneous region, two statistical measures that is to say the bias and root mean squared error (*RMSE)* are used:

$$BIAS(T)(\%) = \frac{100}{N} \sum_{i=1}^{N} \left(\frac{q^R - q_i^R}{q^R} \right) \quad (18)$$

$$RMSE(T)(\%) = 100 \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\frac{q^R - q_i^R}{q^R} \right)^2}$$

where *N* is the number of regions formed during the process of re-sampling stations (*N* is the number of stations in a homogeneous region); q^R is the growth factor return period T determined from the regional growth curve and q_i^R is the growth factor of return period T

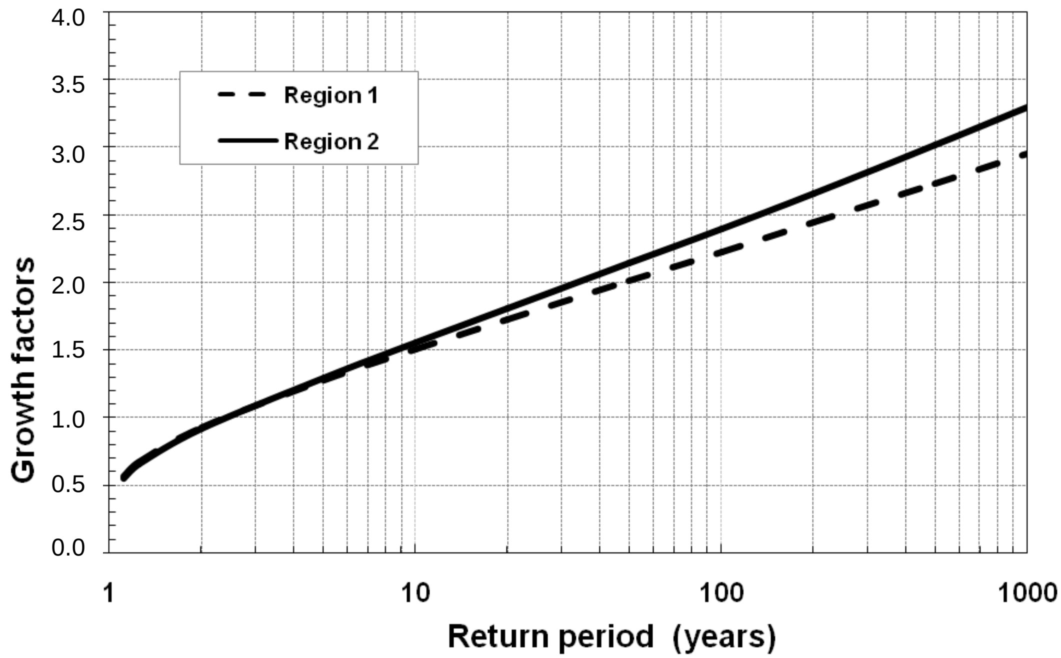

Figure 3. Regional growth curves.

estimated from the data of the i th region obtained during re-sampling.

The variation of the bias and the RMSE versus the period of return for the two homogeneous regions are shown in Figure 4. Bias and *RMSE* of regions 1 are low for all return periods. This means that the growth factors q^R and q_i^R are close and that GEV estimated distribution parameters during re-sampling stations in this region varies very little compared to its regional parameters. For region 2, the bias and *RMSE* are lower and are respectively 0.49 and 2.57% for return period's $T \leq 20$ years. Beyond this level, they increase to reach acceptable values of respectively 1.06 and 5.7% for 1000 years return period.

To test the effectiveness of regional frequency analysis, the values of quantiles estimated from regional and at-site analysis are compared. In at-site analysis, the Gumbel distribution is used since it is the preferred one in the country for estimation of extreme precipitation. The chi-square test was used to test the appropriateness of the Gumbel distribution. This test showed that this distribution can be adopted with a significance level of 5% for all data sets, except those three stations where only 1% is accepted. To evaluate the performance of the regional model, the bias and *RMSE* were calculated for each homogeneous region as follows:

$$BIAS(T)(\%) = \frac{100}{N}\sum_{i=1}^{N}\left(\frac{Q_i^R - Q_i^L}{Q_i^L}\right) \quad (20)$$

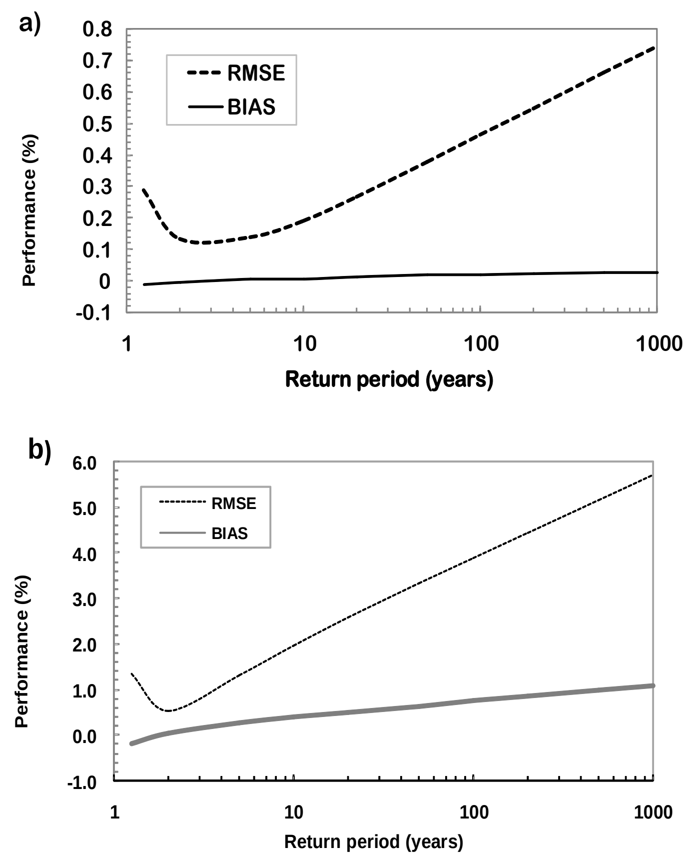

Figure 4. Variation of RMSE and bias related to the regional estimation of growth factors of the two regions based on return periods: a) region 1, b) region 2.

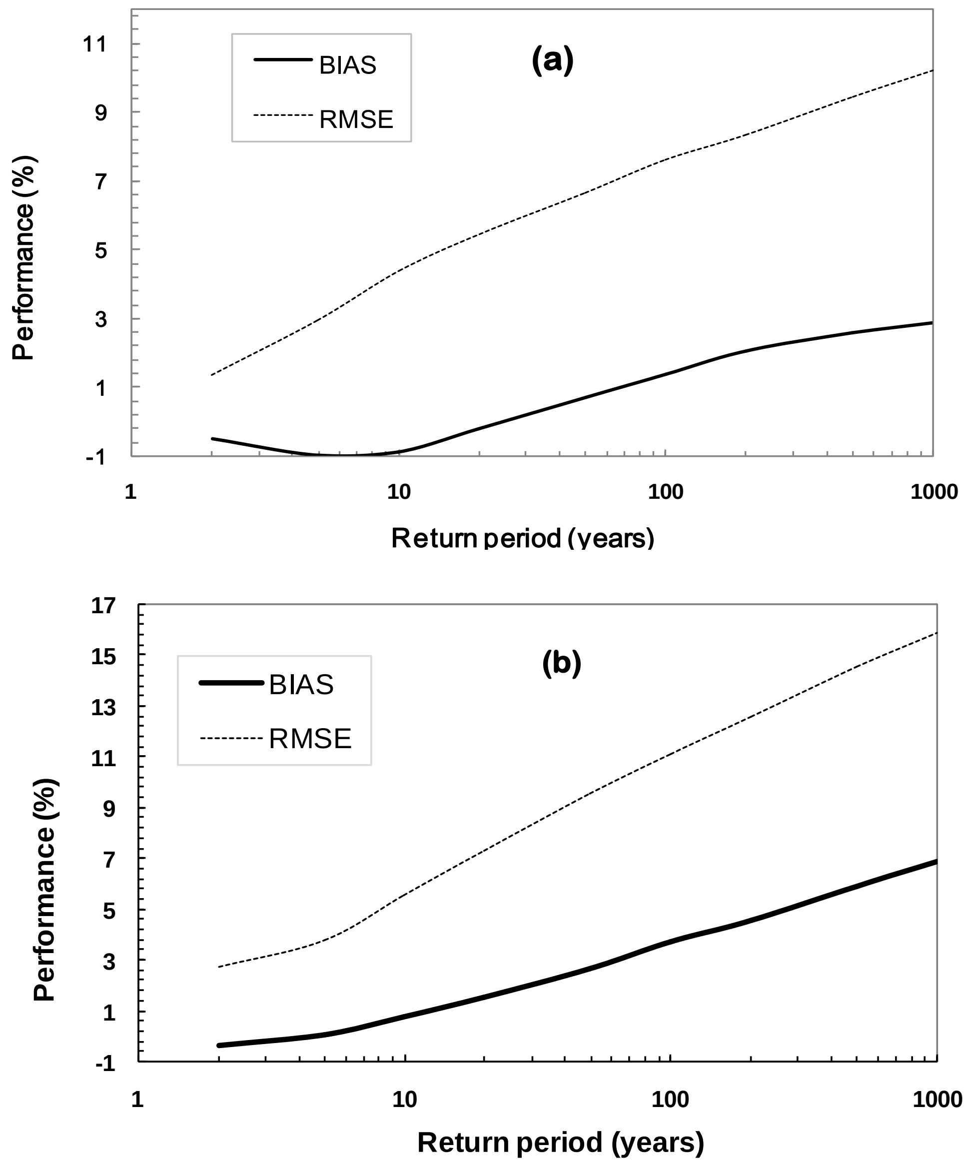

Figure 5. Variation of RMSE and bias related to the regional estimation of quantiles of daily precipitation maximum of three regions according to the return period: a) region 1, b) region 2.

$$RMSE(T)(\%) = 100\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{Q_i^R - Q_i^L}{Q_i^L}\right)^2}, \qquad (21)$$

Where N is the number of stations in a homogeneous region; Q_i^R and Q_i^L are the quantiles of return period T estimated from of regional and at-site analysis in site I, respectively.

Bias and RMSE of quantile different return periods for the two homogeneous regions are shown in Figure 5. Bias of quantiles for the two regions is quite low, especially for Region 1. It follows that the quantiles estimated from regional and at- site analysis are quite similar especially for return periods less than 20 years.

Concerning the RMSEs, its value does not exceed 5.56% for return periods less than 10 years for all regions. Beyond this period it increases progressively with to the return period to reach a maximum value of 15, 87% observed for the region 2 (T = 1000 years). It is noticed that the gap between the bias and *RMSE* is relatively low for all return periods.

Since $RMSE = \sqrt{(BIAS)^2 + (Var)}$, this means that the variance (*Var*) of the error of quantile estimates from the regional information is quite low for all return periods. In overall, the results of the performance study are within the allowable values for particular quantiles return periods

Table 5. Comparison of quantiles estimated from regional and at-site analysis for the three homogeneous regions

Return period (years)	Region 1			Region 2		
	N	Deviation max (mm)	Error max (%)	N	Deviation max (mm)	Error max (%)
5	8	3.91	5.5	15	2.68	5.8
10	8	6.81	10.2	16	5.34	9.4
20	8	10.5	13.8	17	8.08	12.2
50	9	13.9	17.8	18	11.9	15.1
100	10	19.2	20.4	19	15.1	17.1
200	12	22.3	22.7	19	18.8	18.7
500	12	25.5	25.3	21	23.7	20.8
1000	12	32.1	27.1	21	28.0	22.3

N is the number of stations for which the estimated quantile values from the regional analysis are higher than those estimated by the at-site analysis.

ranging from 10 to 100 years which are the most commonly used in urban hydrology and hydraulics as design storm, although the choice of statistical model as local Gumbel distribution was arbitrary.

For most stations the study area, the quantile values of these return periods obtained by the regional analysis are greater than those obtained by adjusting the Gumbel distribution (Table 5). From this table, it can be noted that the maximum quantile deviations ranged from 3.91 to 32.1 mm and the maximum relative error ranged from 5.5 to 27.1% for return periods of 5 to 1000 years. To estimate the quantiles of different return periods in sites without precipitation data of the study area map of iso curves, the mean maximum daily precipitation was performed using the kriging method (Figure 6).

The mean daily maximum precipitation was mapped with only their calculated values for available gauging stations. Although the mean is a good and stable indicator, it could be characterized more precisely by a suitable spatial interpolation. Because of the geographical location of the study area and the presence of relief, the spatial interpolation methods taking into account the topography and the distance from the sea could be used for the mean daily maximum precipitation mapping.

Conclusions

Based on this study the following conclusions are drawn.

1. The investigated area was divided into two homogeneous regions in terms of L-moments ratios using the cluster analysis of site characteristics (longitude, latitude, elevation, mean annual precipitation and mean annual number of rainy days) and the regional homogeneity test. The grouping of stations presents a geographical and climatic consistency. The first region is represented by stations located in the northern part of the investigated area characterized by a Mediterranean climate. The second region stations are located in the southern part of the study area with a semi-arid climate.
2. The GEV, P3, GLO and LN3 distributions were tested. Among these and according to the goodness-of-fit test and the L-moment ratio diagram, the GEV distribution was identified as the most appropriate regional distribution for Region 1 and LN3 distribution for Region 2. The regional parameters of these distributions were estimated using the L-moments approach.
3. Growth curves were established for each homogeneous region. The difference in the curves shapes reflects the difference in the precipitation patterns for the two homogeneous regions. The regional distribution upper tail of the Mediterranean climate region 1 is less pronounced than those of the semi-arid climate region 2. Therefore, to estimate the different return period's precipitation quantiles in a given site of a homogeneous region, the mean precipitation of the site has to be multiplied by the corresponding value of growth factor. To be able to determine the mean of precipitation in sites with unknown data, the distribution map of mean annual maximum daily precipitation was established.
4. To assess the used of regional model efficiency, the inherent bias and *RMSE* of the regional quantiles estimation were calculated. In the at-site frequency analysis, the data sets were fitted to the Gumbel distribution commonly used in Algeria for estimation of extreme precipitation. This performance investigation showed that the bias and RMSE are quite low, especially for return periods $T \leq 100$ years, and that the variance of the relative error of regional quantiles estimation is also low for all regions. The comparison of estimated quantiles from the regional and at-site analysis showed that in most stations the regional model overestimates, in reasonable proportions, the quantiles of different return periods. The obtained results allow us to conclude that the regional

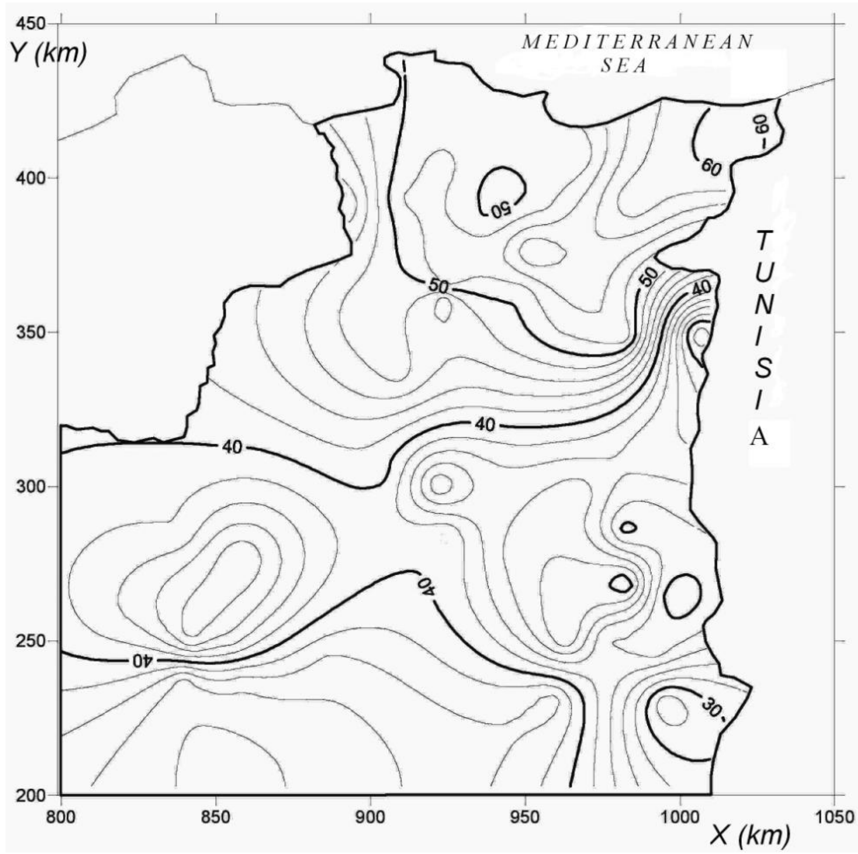

Figure 6. Distribution map of mean maximum daily precipitation of the study area. The map is represented in the Lambert coordinate system (X, Y).

frequency analysis used to estimate extreme daily precipitations is quite robust.

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