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Evidences of relationships between statistics of rainfall extremes and mean annual precipitation: an application for design-storm estimation in northern central Italy

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Abstract

Several hydrological analyses need to be founded on a reliable estimate of the design storm, which is the expected rainfall depth corresponding to a given duration and probability of occurrence, usually expressed in terms of return period. The annual series of precipitation maxima for storm duration ranging from 15 min to 1 day are observed at a dense network of raingauges sited in northern central Italy are statistically analyzed using an approach based on L-moments. The study investigates the statistical properties of rainfall extremes and identifies important relationships between these properties and the mean annual precipitation (MAP). On the basis of these relationships, we develop a regional model for estimating the rainfall depth for a given storm duration and recurrence interval in any location of the study region. The reliability of the regional model is assessed through Monte Carlo simulations. The results are relevant given that the proposed model is able to reproduce the statistical properties of rainfall extremes observed for the study region.

1. Introduction

Design storm are usually estimated by regional frequency analysis of rainfall extremes when there are no measured data for the location of interest, or when data record lengths are short compared to the recurrence interval of interest (Brath et al., 1998; Faulkner, 1999; Brath and Castellarin, 2001).

This study analyses the annual series of precipitation maxima observed at a dense raingauge network located in a wide geographical area of northern central Italy. Several regional frequency analyses of rainfall extremes were performed over the study area analysed here in (Franchini and Galeati, 1994; Brath et al., 1998). These studies proposed subdivisions of the region into homogeneous climatic regions, within which the statistics of rainfall extremes for a given duration are assumed to be constant (Brath and Castellarin, 2001). This assumption contrasts with the findings of other studies, which show that the statistics of rainfall extremes vary systematically with location (Schaefer, 1990; Alila, 1999; Brath et al., 2003). These studies also identified statistically significant relationships between these statistics and the mean annual precipitation (MAP), which was used as a surrogate of geographical location. For instance, Schaefer (1990) and Alila (1999) showed that the coefficients of variation and skewness of rainfall extremes tend to decrease as the local value of MAP increases.

Our analysis has three main goals: (1) investigating the applicability of the studies by Schaefer (1990) and Alila (1999) to the study region; (2) on the basis of the findings obtained at step (1), developing a regional model for estimating design storms for storm duration from 15 min to 1 day in any location of the study area and (3) assessing the reliability of the regional model through Monte Carlo experiments.

2. Index storm procedure

The design of several hydraulic engineering structures need to be based on an estimate of a design storm, which is the expected rainfall depth $h(d,T)$ corresponding to a given duration d and probability of occurrence, usually expressed in terms of return period T.

A regional frequency analysis can be implemented using the index storm procedure (Dalrymple, 1960; Brath et al., 2003). The index storm methodology is based on the identification of homogeneous groups of sites for which $h(d,T)$ can be expressed as the product of two terms, as follows:

$$h(d,T) = m_d h'(d,T) \tag{1}$$

these two terms are a scale factor m_d, which is called index storm, and a dimensionless growth factor $h'(d,T)$, which describes the relationship between the dimensionless storm and the recurrence interval. The index storm, usually assumed equal to the mean of annual rainfall maxima of duration d, is site independent; while the growth factor is assumed to be valid for the entire homogeneous group of basins.

2.1. Growth factor estimation

The classical implementation of the index storm procedure is based on the identification of homogeneous regions where the statistical properties of rainfall extreme, for example coefficient of variation or coefficient of skewness, can be considered constant (see, e.g., Franchini and Galeati, 1994; Brath et al., 1998). Schaefer (1990) and Alila (1999) showed that the statistics of rainfall extremes vary systematically with location and they also identified statistically relationships between these statistics and the MAP. In particular, these studies showed that coefficients of variation and skewness of rainfall extremes tend to decrease as the local value of MAP increases and proposed to enhance the index storm hypothesis for the regional frequency analysis of rainfall extremes by dispensing with the delineation of geographical areas and identifying, instead, as climatically homogeneous subregions those areas which show limited MAP variations.

The study described in this paper investigates the applicability of the findings of Schaefer (1990) and Alila (1999) in a large geographical area of northern central Italy, using annual series of precipitation maxima, for storm duration from 15 min to 1 day, observed by a dense raingauge network with a higher resolution than the networks considered in the previous studies (Schaefer, 1990; Alila, 1999). Several recent regional analyses showed that the Generalised Extreme Value (GEV) distribution (Jenkinson, 1955) is a suitable statistical model for representing the frequency distribution of rainfall extremes over the study area considered (see, e.g., Franchini and Galeati 1994; Brath et al., 1998).

The CDF (cumulative distribution function) of the GEV distribution is written as:

$$F_X(x) = \exp\left\{-\left[1-\frac{k(x-\xi)}{\alpha}\right]^{1/k}\right\}, \text{ for } k \neq 0 \tag{2a}$$

and

$$F_X(x) = \exp\left\{-\exp\left[-\frac{(x-\xi)}{\alpha}\right]\right\}, \text{ for } k = 0 \tag{2b}$$

while the quantile $x(F)$ can be written as:

$$x(F) = \xi + \alpha\left\{1 - (-\log F)^k\right\}/k, \text{ for } k \neq 0 \tag{3a}$$

and

$$x(F) = \xi + \alpha \log(-\log F), \text{ for } k = 0 \tag{3b}$$

where ξ, α, and k are the distribution parameters. As shown by Eqs. (2b) and (3b), when k=0 the GEV distribution is equal to the Gumbel distribution. Combining formulations (2) and (3) can be obtained the relations for the regional growth factor, replacing the variable X with the dimensionless variable X'=X/μ and the parameters α, ξ and $k$with the regional parameters α'=α/μ, ξ'=ξ/μ and k'=k, where the expected value μ is written as:

$$\mu = \xi + \left(\frac{\alpha}{k}\right)[1 - (1+k)]. \tag{4}$$

The parameters α', ξ' and k' can be estimated through the regional procedure based on L-moments (Hosking and Wallis, 1997), using the following relations:

$$k' \approx 7.8590c + 2.9554c^2, \quad \text{with} \quad c = \frac{2}{3 + \text{L-}Cs_R} - \frac{\log 2}{\log 3} \quad \text{and} \tag{5a}$$

$$\alpha' = \frac{\text{L-}Cv_R\, k'}{\left(1 - 2^{-k'}\right)\Gamma(1+k')}, \quad \xi' = 1 - \alpha'\left\{1 - \Gamma(1+k')\right\}/k' \tag{5b}$$

where L-Cv_R and L-Cs_R are, respectively, the 2nd and 3rd order standardised regional L-moments.

2.2. Index storm estimation

The estimation of the index storm m_d can be usually obtained by computing the sample mean of annual rainfall maxima of duration d. If there are no measured data for the site of interest the index storm estimation can be obtained from the observations collected at neighbouring sites through a suitable spatial interpolator (Brath and Castellarin, 2001; Castellarin and Brath, 2002). The uncertainties associated with this estimation procedure can be evaluated through a jack-knife resampling procedure (Brath et al., 2003) structured as follows:

1. we consider the duration d and the number NS of available raingauges where it is possible to calculate m_d from the series of annual maximum depth with duration d (sample mean of annual rainfall maxima);
2. one of these raingauges, say station i, and its corresponding m_d value are removed from the set;
3. we generate a isopluvial map of m_d, interpolating the data of the remaining NS−1 raingauges sites;
4. a jack-knife estimate of m_d for site i is then retrieved from the map identified at step 3;
5. steps 2–4 are repeated NS−1 times, considering in turn one of the remaining raingauges.

The NS empirical value of m_d (i.e., sample means) are then compared with the corresponding values resulting from the jack-knife procedure (i.e. jack-knife estimates). The comparison allows us to draw some considerations on the robustness and reliability of the spatial interpolation, through the following indexes of performance:

$$\begin{aligned} \mathrm{BIAS} &= 1/\mathrm{NS}\sum_{i=1}^{\mathrm{NS}}\left[\left(\hat{m}_{d,jk,i}-\hat{m}_{d,i}\right)/\hat{m}_{d,i}\right]; \\ \mathrm{RMSE} &= \sqrt{1/\mathrm{NS}\sum_{i=1}^{\mathrm{NS}}\left[\left(\hat{m}_{d,jk,i}-\hat{m}_{d,i}\right)/\hat{m}_{d,i}\right]^2} \end{aligned} \quad (6)$$

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where the subscript d, i indicates the sample estimate of m_d for station i, which we assume to be exact, while the subscript d, jk, i indicates the corresponding jack-knife estimate. This procedure can be applied several times, considering different spatial interpolators, to identify the spatial interpolation method that has the minimum uncertainty.

3. Study area and local regime of rainfall extremes

The study area includes the administrative regions of Emilia-Romagna and Marche, in northern central Italy, and occupies 37 200 km^2. The area is bounded by the Po River to the north, the Adriatic Sea to the east, and the Apennine divide to the southwest (see Fig. 1). The north-eastern portion of the study region is mainly flat, while the south-western and coastal parts are predominantly hilly and mountainous.

The database of extreme rainfall consists of the annual series of precipitation maxima with duration d equal to 15 and 30 min; 1, 3, 6, 12 and 24 h and 1 day (i.e., from 09:00 a.m. to 09:00 a.m. of the following day) that were obtained for a dense network of rain gauges from the National Hydrographical Service of Italy (SIMN). The available rainfall data are summarised in Table 1.

The mean annual precipitation (MAP) varies on the study region from about 500 to 2500 mm. Altitude is the factor that most affects the MAP (see Fig. 3), which exceeds 1500 mm starting from altitudes higher than 400 m a.s.l. and exhibits the highest values along the divide of the Apennines.

The diagram of L-moment ratios (see e.g., Hosking and Wallis, 1993) reported in Fig. 2 shows that the theoretical relationship between L skewness (L-*Cs*) and L kurtosis for GEV distribution is very close to the regional L-*Cs* and L kurtosis values for the storm duration of interest, therefore indicating then the GEV distribution is a suitable parent distribution.

The study investigates the applicability of the finding of Schaefer (1990) and Alila (1999) in this particular context, making use of a raingauge network with a higher resolution than the networks considered in the above mentioned papers. In detail, the variability of the sample L moment ratio (Hosking, 1990) of skewness and variation was examined against the variability of MAP. The Fig. 4 shows that the values of L-*Cv* and L-*Cs* of rainfall extremes tend to increase when the MAP value decrease, confirming the results pointed out by Alila (1999).

4. Regional model

4.1. Growth factor estimation

4.1.1. Homogeneous regions

The estimation of the dimensionless growth factor $h'(d,T)$ can also be carried dispensing with the traditional subdivision of the study area into homogeneous regions. In fact, the papers of Schaefer (1990) and Alila (1999) point out that the statistics of rainfall extremes vary systematically with location, showing that all hypotheses of subdivisions into geographical regions lack physical basis. These studies identified statistically significant relationships between these statistics and the MAP, which was used as a surrogate of geographical location.

We developed frequency analysis of rainfall extremes using the MAP values and the L-moments L-*Cs* and L-*Cv*(Hosking and Wallis, 1997), for any considered duration (*d* equal to 15 and 30 min; 1, 3, 6, 12 and 24 h; 1 day). The analysis points out that the L-*Cv* values tend to decrease as the local value of MAP increases (see Figs. 5a and b); for storm duration from 15 min to 6 h the L-Cs values are approximately constant with the geographic position (identified with the MAP value); for longer storm duration the L-*Cs* values tend to decrease as the local value of MAP increases.

In order to quantify the homogeneity degree of groups of stations with similar MAP values, we designed and performed a statistical test which is based upon the approach suggested by Hosking and Wallis (1993). The statistical test assesses the homogeneity of a group of stations according to 3 measures of dispersion of the sample L moments. In this study we consider the first and the second measures:

1. H(1), that focuses on the dispersion of sample L-Cv values;

2. H(2), that focuses on the combined dispersion of sample L-Cv and L-Cs values.

Hosking and Wallis (1993) suggested that the region or group of sites should be considered as acceptably homogeneous if $H<1$; possibly heterogeneous if $1 \leq H < 2$, and definitely heterogeneous if $H \geq 2$.

The homogeneity testing has been developed in the following steps: the set of N raingauges was sorted in ascending order of MAP values; with this ordered set, the $N-n+1$ subset were identified considering, each time, the n closer station in terms of MAP (with n=15, 30, 60); the H(1) values were calculated for each group of 15 and 30 stations, while the H(2) values were calculated for the groups with 30 and 60 stations. The H(1) and H(2) values were assigned to the average MAP value of the subset and the behaviour of H(1) and H(2) values as a function of MAP was then analysed. This analysis (see Fig. 6) shows that the subsets identified according to the MAP value are generally acceptably homogeneous and the H(1) and H(2) values, quantifying the homogeneity degree, are significantly MAP independent.

4.1.2. Empirical regional model for estimating the L-Cv and L-Cs

After testing the regional homogeneity of the climatically similar group of sites (identified according to MAP values) the analysis has been directed to develop an empirical regional model for estimating the regional statistics L-Cs_R and L-Cv_R, which can then be used for estimating the GEV parameters. In detail, we identified a series of statistically significant mathematical relationships between the L-moments and MAP of the form:

$$\text{L-}Cx(\text{MAP}) = a + (b - a) \cdot \exp(-c \cdot \text{MAP}), \quad (7)$$

where L-Cx represents a particular regional L-moment (L-Cs_R or L-Cv_R), relative to the annual maximum series (AMS) of rainfall depth with storm duration d, while a, b, c, with $0 \leq a \leq b$ and $c \geq 0$, are the parameters of the empirical model that have to be estimate through optimization procedure. If $a=b$ and $c=0$, L-Cx in Eq. (7) tends to a constant value. This is the case in which the particular L-moment is MAP independent.

We performed the identification of parameters a, b and c on the basis of the empirical outcomes illustrated in Fig. 5, taking also into account the conclusions of previous studies performed over the same study region (e.g., Franchini and Galeati, 1994; Brath and Franchini, 1999; Castellarin and Brath, 2002), which can be sketched as follows:

1. L-Cs can be considered to be independent of the geographic location (or MAP) for d<6 h;
2. L-Cs can be considered to be independent of geographic location and duration d, for d=15 and 30 min and 1 h;
3. L-Cs can be considered to be the same for duration d=3 and 6 h (Castellarin and Brath, 2002);
4. L-Cv can be considered to be independent of the geographic location (or MAP) for d<1 h, with different values for d=15 and 30 min (Alila, 1999);
5. The relationships between L-Cs, or L-Cv, and the geographic location (or MAP) identified for daily observations can be used also for d≥12 h (Franchini and Galeati, 1994; Brath and Franchini, 1999; Castellarin and Brath, 2002).

Figure 5 shows the identified empirical regional models, while Tables 2 and 3, for L-Cs and L-Cv, respectively, summarise the values of parameters a, b and c for any storm duration. Tables 2 and 3 show that, for AMS with storm duration lower than 1 h, L-Cv increases when duration increases. This outcome confirms the results obtained in previous studies and for different geographic area by Alila (1999).

The reliability of the identified empirical model was assessed through Monte Carlo simulations. In detail, (a) for any station and for each duration, the regional L-*Cv* and the L-*Cs* values were calculated as a function of the local MAP value through model (7) with parameters *a*, *b*, *c* listed in Tables 2 and 3; (b) with these regional L-statistics, regional estimates of the GEV distribution were calculated from the site of interest and the considered duration; (c) this probabilistic model was then used to generate synthetic series with length equal to the corresponding historical series; (d) for these synthetic series the sample L-*Cv* and L-*Cs* were then calculated. We repeated these steps 5000 times, obtaining 5000 sample L-moment values, which we finally used to derive the confidence intervals for testing the significance of the empirical model. Figure 7 shows, for $d=1$ h the confidence intervals derived for L-*Cv* and L-*Cs* and 90% and 95% confidence intervals. Table 4 summarises the results obtained with the Monte Carlo analysis, reporting the percentage of sample L-*Cv* and L-*Cs* values lying out of confidence intervals.

4.2. Estimation of index storm and MAP at ungauged sites

The index storm estimation, m_d, for application of model for estimating the design storm, is a crucial step. So far, we have considered the case of gauged sites where m_d can be calculated as the sample mean of observed annual rainfall maxima. For an ungauged site the direct estimation of m_d is not possible and one can use isoline maps of m_d obtained with spatial interpolation procedure instead (see e.g., Sect. 2.2 and Brath et al., 2003). Some isoline maps are reported in Figs. 8, 9 and 10. The indirect estimation of MAP is also essential for applying to ungauged sites the proposed regional model, as it appears clearly from Eq. (7). MAP can also be estimate at ungauged sites through the use of isoline maps. For this reason, indications on the uncertainty associated with standard spatial interpolation procedures can be very important. We report here the results of a series of resampling experiments aiming at assessing the reliability of m_d and MAP estimates based upon isoline maps. The structure of the resampling procedure is outlined in Sect. 2.2.

The best performances, for estimating m_1 and m_{24} (m_d for duration equal to 1 h and 24 h), were obtained using ordinary kriging with linear variogram (KLV, Kitanidis, 1993), considering no more than 8 stations located at no more than 40 km from the site of interest. Table 5 shows the RMSE and BIAS values that were obtained estimating for 132 stations with at least 30 years of observation. The box-plot diagram (Fig. 11) shows the relative error distributions for the estimation of m_1 and m_{24} and the two duration considered. In the same way, the reliability of the MAP estimation has been studied for the study area, testing the performances of different spatial interpolation procedure. Among these the ordinary kriging with linear variogram produce a efficient estimation also for the MAP.

Given that altitude is the factor that most affects MAP (see Fig. 3), we also consider the ordinary kriging of relative residuals obtained from a suitable linear regression model between elevation and MAP (see Fig. 3) as a procedure for estimating MAP at ungauged sites. The cross validation produced the best performance indexes combining a linear regressive model, for representing the relationship elevation-MAP, with a KLV spatial interpolation of relative residuals.

Table 5 shows the values of RMSE and BIAS obtained with a direct geographic interpolation of MAP (MAP) or an interpolation of the relative residuals of the regression model (MAP_r). The box-plots (Fig. 11) show the relative error distributions of the cross validation estimated value for the two interpolator.

The cross validation of the m_1 and m_{24} indirect estimates produced similar statistical index of performance. In detail, the box-plots (Fig. 11) show rather high values of the maximum relative error (close to 40%) and indicate that about half of the jack-knife estimates values has got relative errors bigger than 7–8%.

It is interesting to observe (Table 5 and Fig. 11) that the uncertainty of the ordinary kriging of relative residuals (MAP_r) is approximately the same, or inferior, as the uncertainty of ordinary kriging of the empirical MAP values (MAP). This indicates that taking explicitly into account the orographic effect on MAP values does not improve the estimation performances.

The results are obviously connected with the geographic area considered herein and the particular raingauge network of our study. Nevertheless, the analysis points out relevant suggestions on the uncertainty estimation of m_d and MAP obtained through spatial interpolation procedures. First, the reliability level is analogous for all rainfall indexes considered in the study (i.e., m_1, m_{24} and MAP) but depends on the geostatistical spatial interpolator. Second, the cross-validation procedure applied here in allowed a quantification of the estimation uncertainty, which can be effectively taken into account while estimating of m_d and MAP in ungauged sites (see Table 5 and Fig. 11).

5. Design storm estimation in ungauged sites

We provide in this section a brief summary illustrating the application procedure of the proposed model, The model can be applied at any site in the study region for d equal to 15 and 30 min; 1, 3, 6, 12 and 24 h and 1 day. For each storm duration d and return period T, the design storm $h(d,T)$ can be evaluate by the following steps:

a) Estimate the local value of the mean annual precipitation, MAP for the site of interest. If the site is ungauged one can use a spatial interpolation procedure (see e.g., Fig. 3);

b) Estimate the mean of annual rainfall maxima with duration d, m_d. If the site is ungauged one can use a spatial interpolation procedure (see e.g., Figs. 8–10);

c) Compute as a function of the local MAP value (step a) a regional L-Cs_R, with model (7) and parameters a, b and c reported in Table 2;

d) Compute as a function of the local MAP value (step a) a regional L-Cv_R, with model (7) and parameters a, b and c reported in Table 3;

e) Estimate the regional GEV parameters α', ξ' and k', through Eqs. (5a) and (5b) using the L-Cs_R and L-Cv_R values estimated at steps c and d;

f) Compute $h'(d,T)$ using the parameters α', ξ' and k' and the probability F equal to $1-1/T$, where T is the return period in years;

g) Compute an estimate of the design storm $h(d,T)$ as the product $h'(d,T)m_d$.

6. Conclusions

The paper presents a regional frequency analysis that was carried out using the annual maximum series of rainfall depth for storm duration ranging from 15 min to 1 day, observed for a dense network of raingauges sited in northern central Italy.

The study investigated the statistical properties of rainfall extremes using an approach based on L-moments, and identified at a regional scale important relations between these statistics and mean annual precipitation (MAP) which are validated.

Previous studies showed that the statistics of rainfall extremes vary systematically with location and these studies also identified statistically significant relationships between these statistics and MAP, which was used as a surrogate of geographical location. Schaefer (1990) and Alila (1999) showed that the coefficients of variation and skewness of rainfall extremes tend to decrease as the local value of MAP increases. Our study confirmed in part these findings on a different geographic area.

A statistical homogeneity test has been performed to evaluate the homogeneity for stations with similar MAP value. In detail, the statistical homogeneity test in this study followed an approach using L moments, as suggested by Hosking and Wallis (1993). The study points out that the MAP can be used as a valid alternative to the geographic position in order to identify homogeneous groups of sites.

We developed an empirical regional model for estimating design storm in northern central Italy and we assessed the model reliability through an extensive cross-validation. The results are relevant given that the proposed model is able to reproduce the statistical properties of rainfall extremes observed for the study region.

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Table 1. Study area: number of raingauges and annual maximum rainfall data.

Duration	Criterium	Number of Gauges	Number of data
daily	$N \geq 30$	394	20 557
hourly	$N \geq 30$	125	5945
30 min	$N \geq 5$	186	3430
15 min	$N \geq 5$	152	1810

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Table 2. Coefficients *a*, *b* and *c* of the regional model (7), regional values for estimating L-Cs_R.

Duration	a	b	c
15 min$\leq d \leq$1 h	0.1999	0.1999	0
3 h$\leq d \leq$6 h	0.2318	0.2318	0
12 h$\leq d \leq$24 h, d=1 d	0.1824	4.7240	0.0061

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Table 3. Coefficients *a*, *b* and *c* of the regional model (7), regional values for estimating L-Cv_R.

Duration	*a*	*b*	*c*
15 min	0.1539	0.1539	0
30 min	0.1893	0.1893	0
1 h	0.1978	0.6255	0.0038
3 h	0.1856	0.8352	0.0042
6 h	0.1741	0.8436	0.0042
12 h$\leq d \leq$24 h, d=1 d	0.1706	0.7694	0.0040

Table 4. Percentage of the sample values of L-*Cv* and L-*Cs* lying out of the confidence intervals.

Significance level	L-*Cs*	L-*Cv*
5%	4.20%	4.80%
10%	8.50%	9.80%

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Table 5. RMSE and BIAS obtained for the estimation of rainfall indexes for 132 station with at least 30 years of observation.

	KLV application	RMSE	BIAS
m_1	Empirical values	11.2%	1.0%
m_{24}	Empirical values	11.9%	2.9%
MAP	Empirical values	9.9%	1.2%
MAP_r	Relative residuals interpolation	11.8%	1.3%

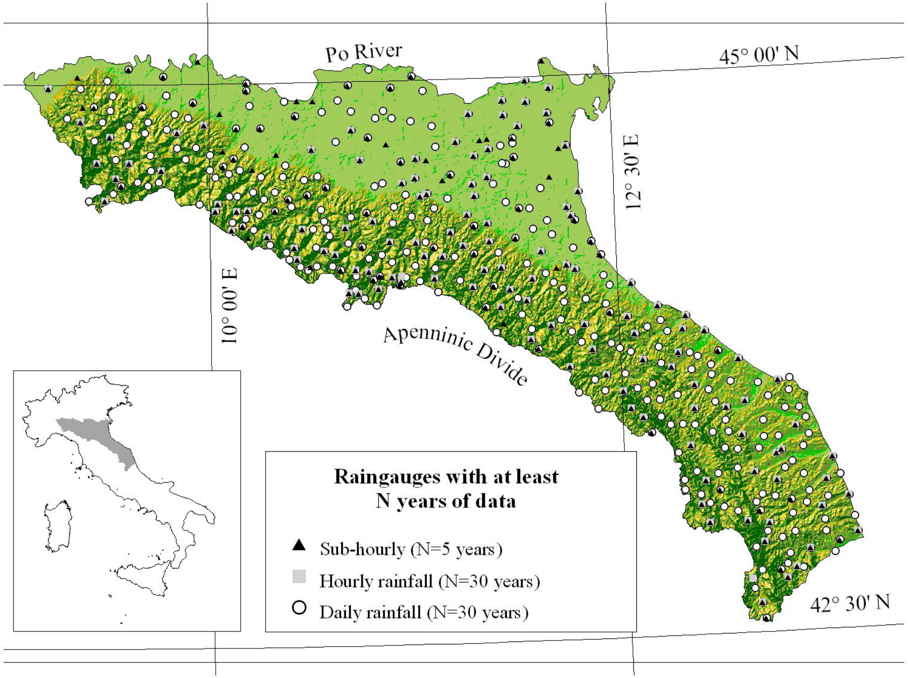

Fig. 1. Study area and location of raingauges for different values of the minimum record length.

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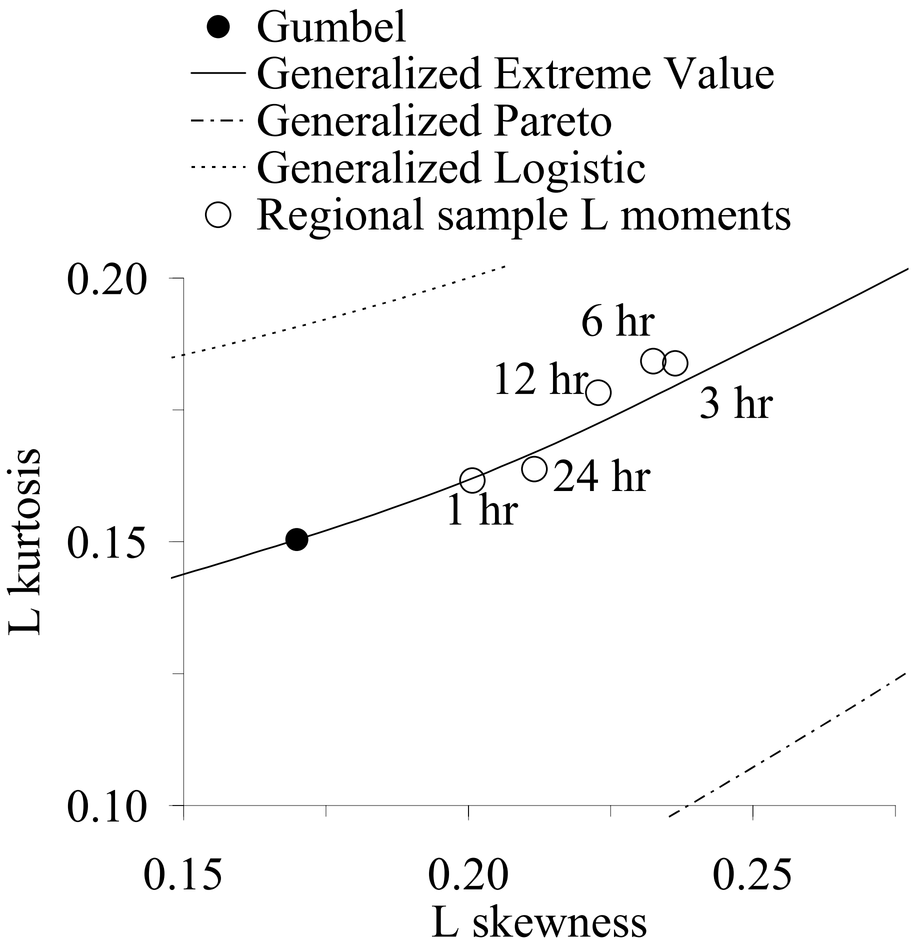

Fig. 2. Diagram of L-moment ratios for the application data.

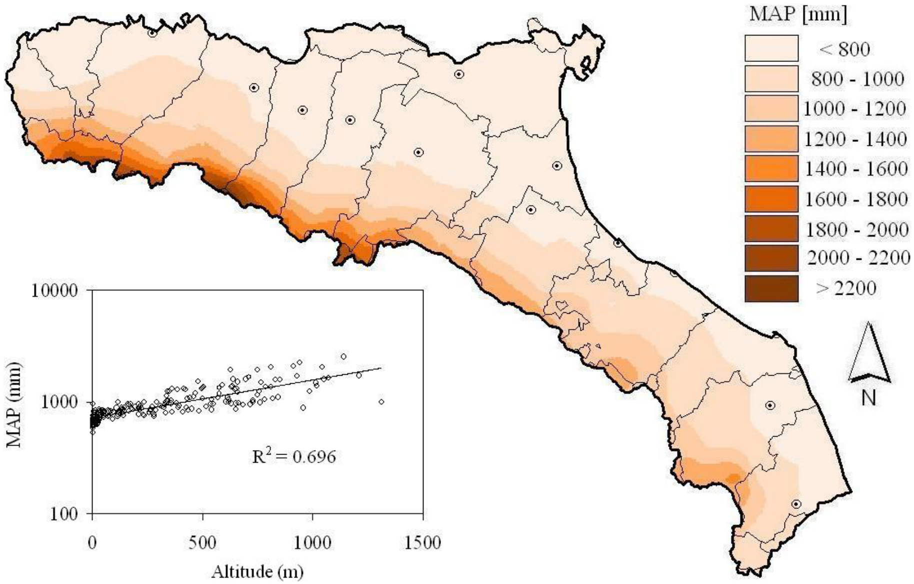

Fig. 3. Mean annual precipitation MAP (mm). MAP versus altitude (m a.s.l.).

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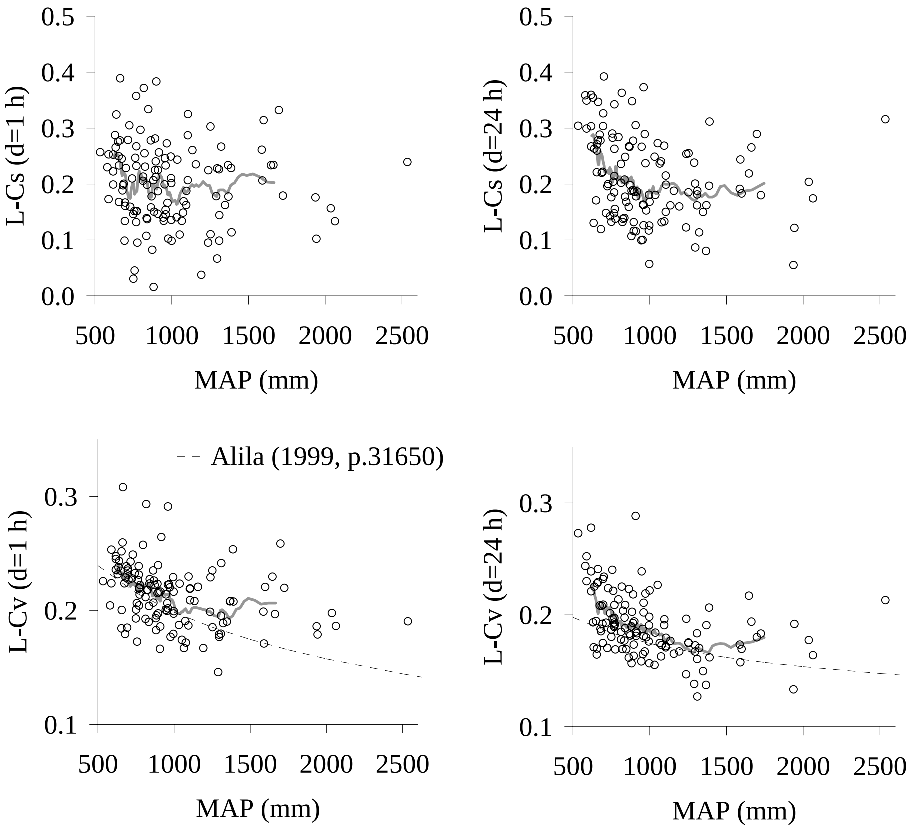

Fig. 4. Sample L-*Cs* and L-*Cv* vs. mean annual precipitation MAP (mm) for durations d=1 h and d=24 h; moving weighted average curves of L moments for raingauges; relationships between L-*Cv* and MAP identified by Alila (1999).

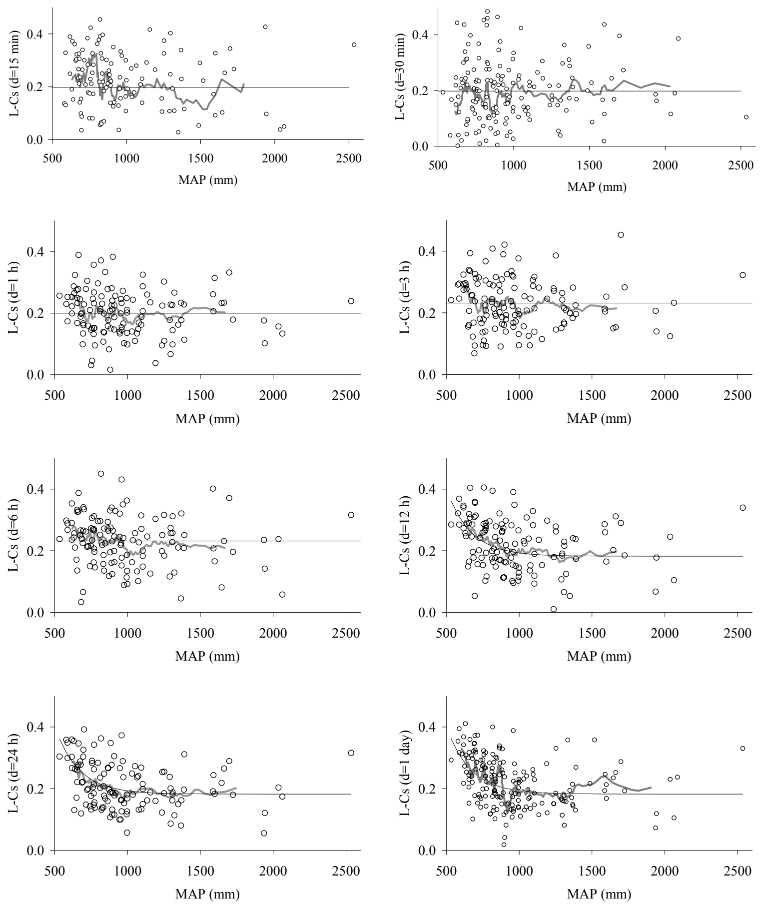

Fig. 5a. Sample L-*Cs* versus MAP (mm) for durations between 15 min and 1 day (circles), moving weighted average curves (grey lines) and empirical regional model (black lines).

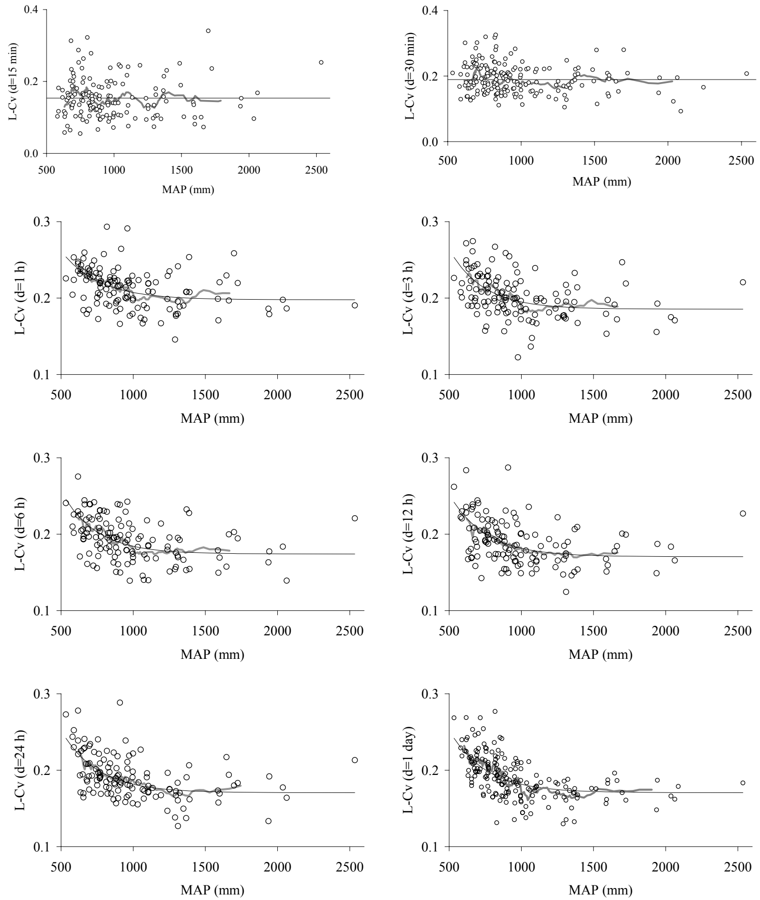

Fig. 5b. Sample L-*Cv* versus MAP (mm) for durations between 15 min and 1 day (circles), moving weighted average curves (grey lines) and empirical regional model (black lines).

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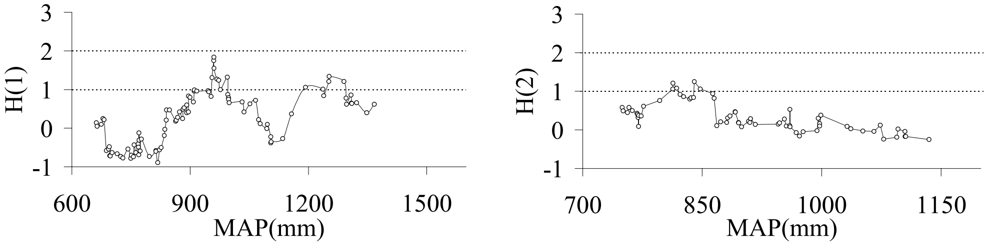

Fig. 6. Heterogeneity measures versus MAP: H(1) values for groups of 30 stations and d=6 h (H(1)=3.41 for the entire study region); H(2) values for groups of 60 stations and d=24 h (H(2)=1.73 for the entire study region).

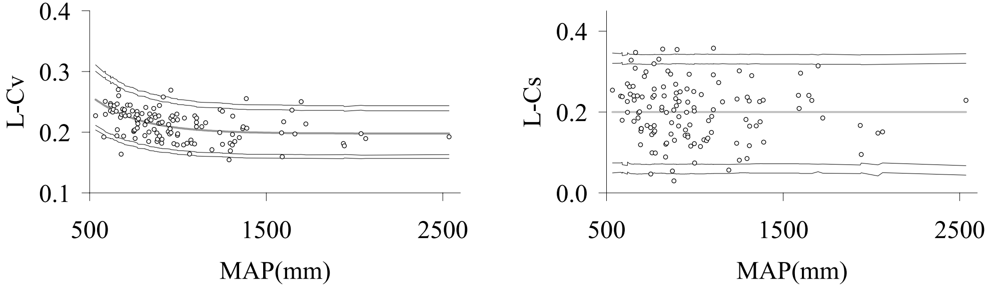

Fig. 7. Empirical models of L-Cs_R and L-Cv_R for d=1 h (grey lines); sample L-*Cs* and L-*Cv* (circles); 90 and 95% confidence intervals obtained trough Monte Carlo experiments (black lines).

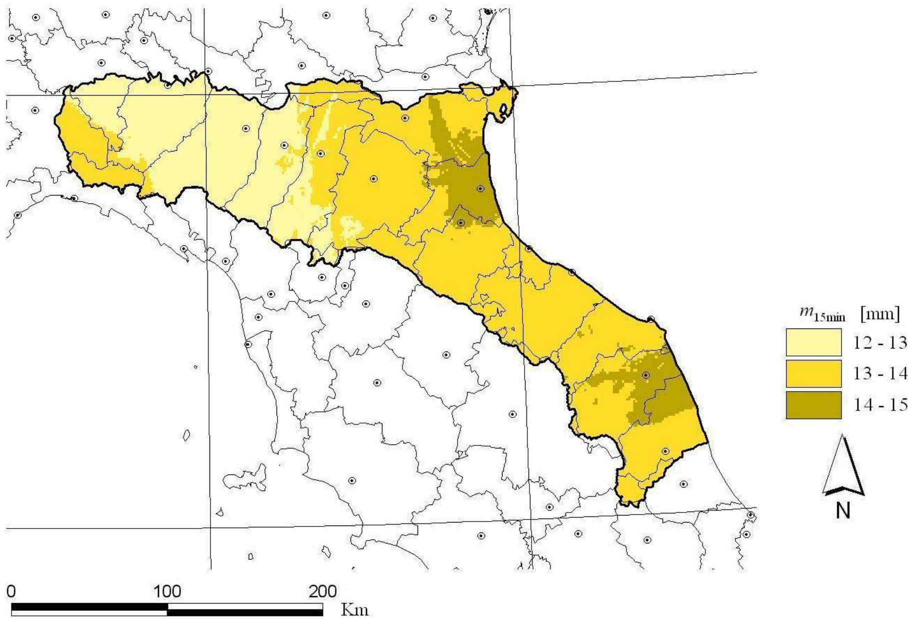

Fig. 8. Mean annual rainfall maxima for duration d=15 min.

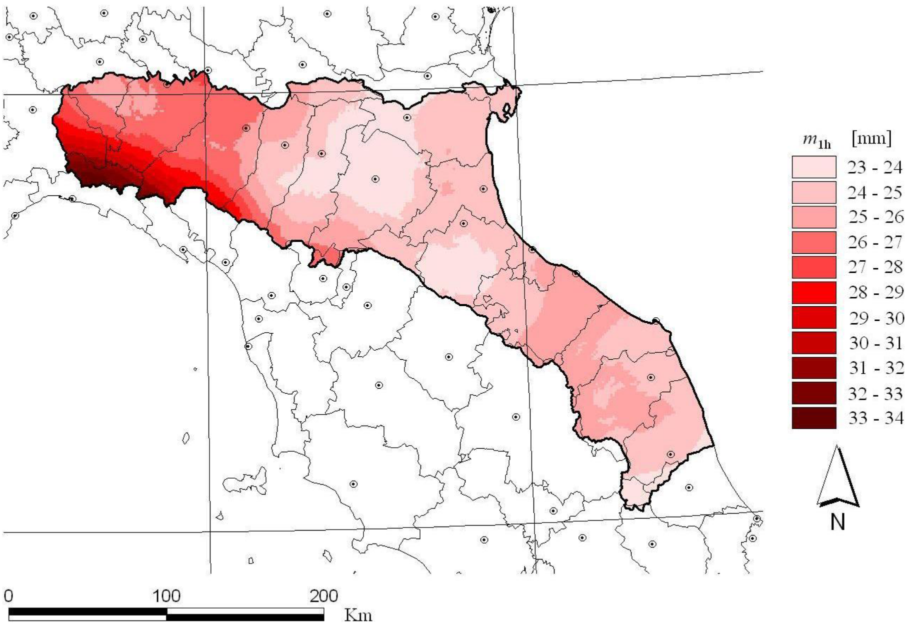

Fig. 9. Mean annual rainfall maxima for duration d=1 h.

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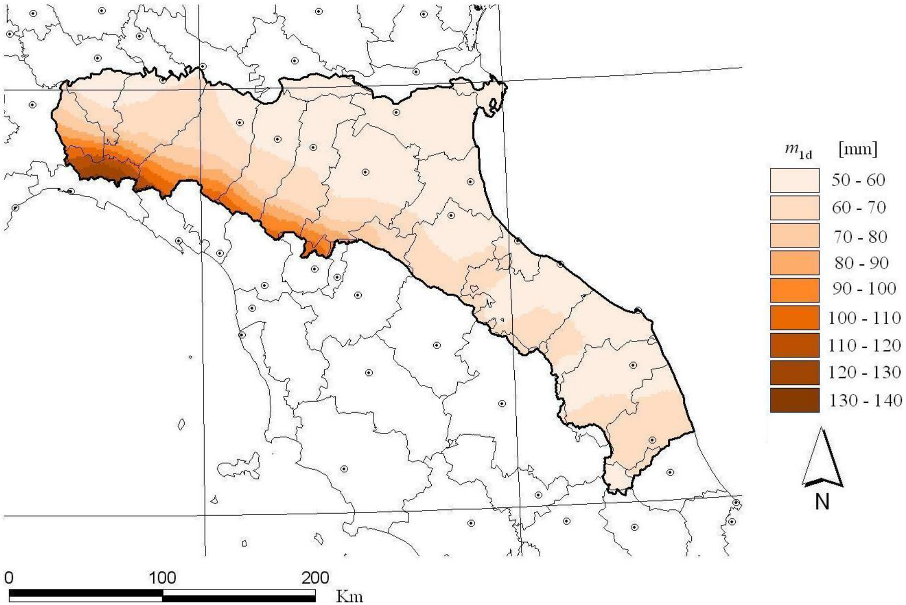

Fig. 10. Mean annual rainfall maxima for duration d=1 day.

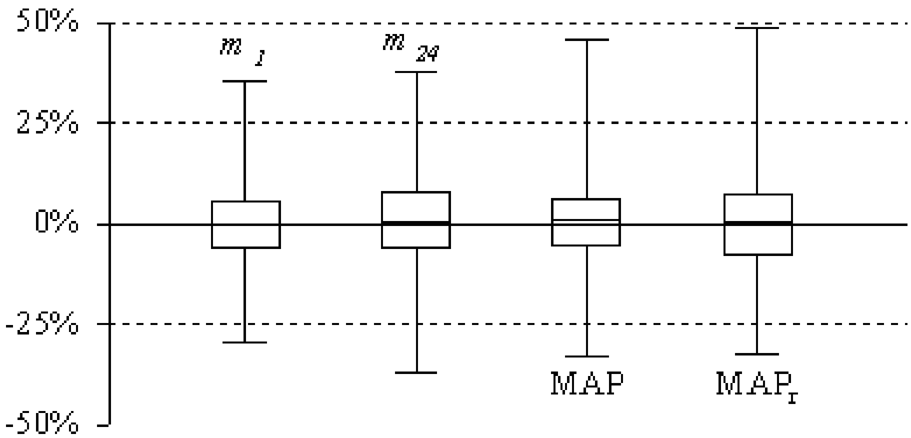

Fig. 11. Boxplots: minimum and maximum values, first, second (median) and third quartiles of the distributions of the relative error for the estimation of m_1, m_{24} and MAP.

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Regional model for design storm estimation

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