Hydrol. Earth Syst. Sci. Discuss., 10, 6321–6358, 2013 www.hydrol-earth-syst-sci-discuss.net/10/6321/2013/ doi:10.5194/hessd-10-6321-2013 © Author(s) 2013. CC Attribution 3.0 License.



This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

On the quest for a pan-European flood frequency distribution: effect of scale and climate

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Received: 2 May 2013 - Accepted: 6 May 2013 - Published: 22 May 2013

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Published by Copernicus Publications on behalf of the European Geosciences Union.

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Abstract

This study addresses the question of the existence of a parent flood frequency distribution on a European scale and aims to better understand the effect of catchment scale and climate on the statistical properties of regional flood frequency distributions.

- A new database of L-moment ratios of annual maximum series (AMS) of peak discharges from 4105 catchments was compiled by joining 13 national datasets. Using this database and additional Monte Carlo simulations, the *Generalised Extreme Value* (GEV) distribution appears as a potential pan-European flood frequency distribution, being the 3-parameter statistical model with the closest resemblance to the estimated
- ¹⁰ average of the sample L-moment ratios, but failing to represent the kurtosis dispersion, especially for high skewness values. A more detailed investigation performed on a subset of the database (Austria, Italy and Slovakia, involving a total of 813 catchments with more than 25 yr of record length) confirms that the GEV distribution provides a better representation of the averaged sample L-moment ratios compared to the other distribution.
- ¹⁵ butions considered, for catchments with medium to high values of mean annual precipitation (MAP) independently of catchment area, while the *3-parameter Lognormal* distribution is probably a more appropriate choice for dry (low MAP) intermediate-sized catchments, which presented higher skewness values. Sample L-moment ratios do not follow systematically any of the theoretical 2-parameter distributions. In particular, the
- averaged values of L-coefficient of skewness (L-Cs) are always larger than Gumbel's fixed L-Cs. The results presented in this paper contribute to progress towards the definition of a set of pan-European flood frequency distributions and to assess possible effects of environmental change on its properties.

1 Introduction

²⁵ The first step for any assessment of the flooding potential or flood-hazard is the estimation of the design flood associated with a given annual exceedance probability,





often quoted in terms of a recurrence interval T measured in yr. This information is most commonly obtained using flood frequency estimation techniques based on statistical analyses of series of observed flood peak discharges. Unsurprisingly, extreme flood events are seldom observed locally, and hydrologists have little or no chance of

- ⁵ gathering an adequate sample of catastrophes for analysis, especially for prediction at ungauged sites, with the exception of post-event surveys (see e.g. Marchi et al., 2010; Gaume et al., 2010). It is therefore important that effective and practical procedures are available, assisting hydrologists in making inference about flood risk; both at gauged and at ungauged sites (Blöschl et al., 2013).
- ¹⁰ When only an estimate of the peak flow value is needed, direct and regional statistical extreme value analysis of river flow data can be used, depending on data availability. However, it is well-known that such estimates can be associated with a high degree of uncertainty, and it is therefore important to ensure that decisions are robust and are made based on as much information as possible (Viglione et al., 2013; Merz
- and Blöschl, 2008a,b; Martins and Stedinger, 2001). The choice of method for flood frequency estimation in any particular situation is often dictated by factors such as national or institutional tradition, modeller expertise, complexity and objective of study, legislative requirements, and data availability (Castellarin et al., 2012). It is usual though, to assume the existence of a parent flood frequency distribution within a certain region.
- The question of the existence itself of a parent distribution has puzzled hydrologists for many years and substantial work has been done in order to verify or falsify this hypothesis. Matalas et al. (1975) found that the variance of sample coefficient of skewness was always higher. for observed data than for simulated flood peaks for a set of considered parent distributions, calling this phenomenon "skew separation". They further
- showed that it could not be attributed either to small sample properties of the skewness estimator or to autocorrelation of the flood peak series. Dawdy and Gupta (1995) related the magnitude of this "skew separation" to the scaling structure of flood peaks and the heterogeneity among regions on the study from Matalas et al. (1975). Other authors have also shown that different distributions than those considered in Matalas





et al. (1975) were able to reproduce the skewness variability, namely Houghton (1978) for the *Wakeby* distribution and Rossi et al. (1984) for the TCEV distribution; while Ashkar et al. (1992) and Bobée et al. (1993) provide criticism on using the separation of skewness for choosing the type of distribution to be used in regional flood frequency

⁵ analysis and give more importance to the step of the definition of homogeneous regions in order to avoid mixing of different skewness values from different populations.

On an applied level, specific procedures for flood frequency analysis in the past have been usually developed and parametrized for individual countries, and sometimes even within national administrative regions. In particular, existing guidelines give recommen-

- dations on which statistical model, i.e. regional or local parent distribution, to use and this choice could have an important effect on the estimation of high return period flood quantiles due to the different behaviour of the tails of the distribution functions (see e.g. El Adlouni et al., 2008). In some occasions, this recommendations are not justified by any evidence from the local data, or are simply inspired or adapted from analogue
- ¹⁵ guidelines in other countries. Keeping in mind the need for more effective use of existing data, a key scientific and practical challenge for improved risk assessment is a pan-European comparison and evaluation of the consistency of estimates across methods, physiographic regions and a variety of spatial scales in order to ensure comparable flood frequency estimates and safety measures across Europe, as requested by the Directive 2007/60/EC. In fact, it is of utmost importance for the implementation of
- the Flood Directive that state of the art and harmonized methods are used to estimate extreme flood frequencies to obtain consistent values for locations where rivers cross national borders.

This paper exploits the first available inventory of data and statistical methods for flood frequency estimation across Europe, compiled with the aim to homogenize and harmonize the current level of knowledge on the approach to flood frequency estimation used across Europe. The inventory has been created as part of COST Action ES0901 (European Procedures for Flood Frequency Estimation – FloodFreq), which is a European Commission funded project that develops a network of experts, involved





in nationally funded flood frequency estimation research projects. Their main task is to undertake a pan-European comparison and evaluation of methods of flood frequency estimation under the various climatologic and geographic conditions found in Europe, and promoting a synergic approach to flood-hazard assessment, as requested by the European Flood Directive (Kjeldsen, 2011; Castellarin et al., 2012).

The paper addresses explicitly the question of the existence of a parent flood frequency distribution on a European scale. It presents the results of an assessment based on the analysis of a newly established pan-European database of annual maximum series (AMS) of flood flows and their statistical characteristics compiled for the EloodEreg project in order to find the most suitable frequency distribution for mod-

FloodFreq project, in order to find the most suitable frequency distribution for modelling the flood frequency regime in Europe. Additionally, a subset of the data is used to study the control of commonly available physiographic and climatic characteristics (catchment size and mean annual precipitation) on the properties of the underlying probability distribution of flood flow.

15 2 Inventory of data and methods and European flood database

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The first phase of the FloodFreq COST Action focused on the compilation of inventories of dataset and methods for flood frequency estimation at a European level. An extensive survey was conducted among 15 European countries in order to assess the availability of flood data, catchment descriptors and investigate the existence of national guidelines for flood frequency estimation. Particularly, if these guidelines existed, related to the issue of large-scale underlying parent distributions, it was of interest if any type of flood frequency distribution was recommended. The main results of the survey relevant for this paper are presented below.



2.1 European flood database

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The assessment of flood data availability at national level for the 15 European countries included in the survey showed that annual maximum series (AMS) of flood flows are the most common standard. Therefore it was decided to focus on a collection of 5 AMS of flood flows considering daily flows, as well as instantaneous peak flows where available.

From the 15 surveyed countries, 13 agreed to share flood data in the frame of the FloodFreq COST Action. Due to national policies and regulations that restrict the publication of some of these data, the flood data themselves were summarized into statistical moments. In particular, the AMS for a total of 4105 sites was characterized by the number of observations n and sample L-moment ratios of orders 2 to 4 (i.e. sample

- L-coefficient of variation, sample L-coefficient of skewness and sample L-coefficient of kurtosis). Table 1 contains a summary of the national AMS datasets available in the database. The use of L-moments instead of conventional moments offers several ad-
- vantages such as the possibility of characterizing a wider range of distributions, smaller bias and higher robustness of the parameter estimators when applied to short samples (Vogel and Fennessey, 1993). For more details on L-moments see e.g. Hosking (1990), Hosking and Wallis (1997).

2.2 National guidelines for flood frequency estimation

- National guidelines for flood frequency estimation are available in 9 out of the 15 surveyed countries. In Germany, reference studies are available at the level of the federal states, and in Belgium for the Flemish part only. Public agencies and institutions in six countries provide recommendations as to the most suitable parent distributions to be used for flood frequency analysis, but in general such guidance appears to be sparse.
- In a number of countries, the *Generalized Extreme Value* (GEV) distribution is among the recommended choices (e.g. Austria, Germany, Italy, Spain), but a variety of 2-, 3-or 4-parameter distributions are also used, including: the *Gumbel* (GUM) distribution in





Finland and Spain, the 3-parameter *Generalized Pareto* (GPA) distribution in Belgium, the 3-parameter *Generalized Logistic* (GLO) distribution in the UK, or the 4-parameter *Two Component Extreme Value Distribution* (TCEV) in Italy and Spain. The Slovenian Environment Agency uses five different distributions (*Normal, Lognormal, Pearson type*)

- ⁵ *3, log-Pearson type 3* and *Gumbel*) implemented in their own software DIST. In Slovakia, the *Gamma, 3-parameter Lognormal, log-Pearson type 3* and GEV distributions are often used. Six countries reported that they have no standard parent distribution and the choice of an appropriate model depends mostly on the region where the analysis is undertaken (Castellarin et al., 2012).
- The existence of some preferred statistical models, provides a motivation for a further investigation into potential candidates for a pan-European flood frequency distribution, taking advantage of the uniquely extensive flood-data collection compiled in this study (see Table 1 and Fig. 1a). In addition, a subset of the FloodFreq database was selected to investigate in more detail the extent of catchment and climate controls on the characteristics of the flood series, and the influence of these factors on the type of parent
- distribution function.

3 A pan-European flood frequency distribution

3.1 L-moment ratio diagram framework

A continuing challenge in hydrology is the selection of an appropriate probability dis tribution function (pdf) to describe streamflow frequency regimes, and flood frequency regime in particular. The preliminary analyses of the FloodFreq database address this very issue in the L-moment working environment and, in particular, through the use of L-moment ratio diagrams which enables graphical identification of a suitable regional parent distribution among several 2- and 3-parameter candidates. (see e.g. Hosking
 and Wallis, 1997). The scientific literature seems to agree on the value of L-moment ratio diagrams for guiding the selection of a regional parent distribution (e.g. Vogel and



Fennessey, 1993; Vogel and Wilson, 1996; Peel et al., 2001; Strupczewski et al., 2011). An additional advantage of the diagrams is that L-moments are particularly suitable for short samples often associated with annual flood sequences, as sample L-moments tend to be less biased than the corresponding estimators of conventional moments (Vogel and Fennessey, 1993).

Two types of L-moment ratio diagrams are commonly used in the literature to assess the goodness of fit of regional parent distributions, (i) a diagram plotting the L-coefficient of variation against the L-coefficient of skewness (or L-Cs - L-Cv diagram), and (ii) a plot of the L-coefficients of kurtosis against the L-coefficient of skewness (or L-Cs - L-Ck diagram). The former is used to assess the suitability of various 2-parameter distributions, while the latter version of the diagram is more commonly used when 3-

parameter distributions are considered. The suitability of various candidate parents is assessed by analysing how close the cloud of sample L-moments computed for the study region lies, relative to the lines corresponding to the different theoretical models.

3.2 Results for the entire FloodFreq database

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Figure 1a shows the L-*Cs* – L-*Ck* diagram for the entire FloodFreq dataset (see also Table 1) and includes the sample L-moment ratios for all of the catchments in the dataset (light grey circles), together with four lines illustrating the theoretical relationship between L-*Cs* and L-*Ck* for the 3-parameter frequency distributions that, as highlighted by the survey, were preferentially recommended in the national guidelines, namely the *Generalized Extreme Value* (GEV), *Generalized Logistic* (GLO) and *3-parameter Lognormal* (LN3), and *Pearson Type 3* (PE3).

To reduce some of the noise that is present in the empirical data due to sampling uncertainty and better determine which of the four considered 3-parameter distributions ²⁵ better represents the statistical properties of the sample, a record length weighted moving average (WMA) is included in Fig. 1a. In particular, the WMA is computed by taking the weighted mean of the 200 neighbouring sample L-*Cs* values, and plotting it against the weighted mean of the corresponding 200 sample L-*Ck* values. Each sample





L-moment ratio is weighted proportionally to the record length to reduce the impact of sampling variability from short records. The WMA values in Fig. 1a follow closer the theoretical relationship between L-Cs and L-Ck of the GEV distribution, than of any of the other considered distributions. The position of the WMA indicates therefore that

the GEV distribution might be a better candidate for describing the frequency regime of annual maximum floods at a pan-European level, compared to the other three extreme value distributions studied.

3.3 Monte Carlo simulations

The GEV is the statistical model that best represents the averaged statistical properties of the entire database, if compared to the other 3-parameter distributions. In order to falsify or verify the hypothesis that the GEV could actually be the underlying pan-European flood frequency distribution, the spread of the observed data has to be compared with the theoretical scenario where all stations represent random samples drawn from GEV distributions with a variety of sample lengths, skewness and kurtosis

- values. This reference scenario was set up via Monte Carlo simulations. Specifically, a total of 50 000 artificial Europes are simulated as follows. L-Cs of flood flows sequences is assumed to vary randomly between sites as described by a Normal distribution with mean equal to 0.213 and standard deviation equal to 0.155, and the record lengths distribution across Europe is modelled as a 3-parameter Gamma. All param-
- eters from both distributions were estimated from the characteristics of the observed distributions of the database. The types of distribution were chosen based on their respective probabilistic plots. Record length and L-*Cs* are assumed independent, as no significant correlation is found between the sample values. Then, for each one of the 50 000 simulations, two samples of length 4015 elements are generated from the pre-
- viously defined *Gamma* and *Normal* distributions for the record lengths and population L-*Cs* values, representing the properties of each of the stations in the simulated Europes. The population L-*Ck* values are then obtained from the functional relationship between skewness and kurtosis for the GEV model, and without loss of generality, the





mean and L-*Cv* values are both set to 1. For each of the 4015 virtual stations, a sample from a GEV distribution is generated, with each of the previously simulated population properties. Finally, the sample L-moment ratios are computed for each of the generated GEV stations, which will not necessarily be located on the theoretical GEV line on the L-Cs - L-Ck diagram, due to both sample variability (finite record lengths) and biases

in the sample estimators of the L-moment ratios (see e.g. Hosking and Wallis, 1997, p. 29).

To ease the interpretation of the results, the L-*Cs* – L-*Ck* values for both the observed data and the simulations are binned into five equidistant classes between L-*Cs* equal to 0 and 0.55, and the spread of the L-moment ratios is represented by the 10, 30, 50, 70 and 90 % percentile of the L-*Ck* values for each bin and shown in the boxplots of Fig. 1b. For the observed data, every bin is associated to only one value of the 10, 30, 50, 70 and 90 % percentile respectively, but in the case of the simulations we obtain 50 000 values for each of the percentiles, one for each of the simulated Europes.

¹⁵ This means, we obtain sample distributions for all of the quantiles, as is shown for the case of the median in Fig. 1b. The 10, 30, 70 and 90 % percentiles for the simulations have their corresponding sample distributions, but in Fig. 1b only their mean values are represented for the sake of clarity.

In the Monte Carlo simulations, the explicit assumption that the underlying parent distribution of all stations in Europe is given by the GEV model is made, and this assumption will be verified or falsified with the classical approach of statistical hypothesis testing. We define the null hypothesis H₀ as "For the *i*th bin, the *j*% percentile of the sample L-*Ck* distribution from the data is not significantly different to the *j*% percentile in the same bin, for all stations having been randomly drawn from GEV distributions".

For each of the percentiles there is a sample distribution (from the simulations), and an observed value (from the observed data) available, so we can calculate the associated p values, set a significance level and reject or accept the null hypothesis for all the quantiles. Table 2 shows these calculated p values for the plotted quantiles in Fig. 1b. For a 5% significance level, we cannot reject the null hypothesis that the medians,





for all 5 bins, are equal to those from a randomly generated GEV Europe, which is an equivalent result to that of Sect. 3.2 and shown in Fig. 1a on the weighted moving averages, i.e. that the mean or median L-*Cs*–L-*Ck* behaviour is consistently explained by the GEV distribution. The results for the spread of the L-*Ck* values show that we can not reject the null hypothesis of the GEV distribution explaining the observed dispersion of L-*Ck* under the median, for L-*Cs* values smaller than 0.33. For all five bins,

the GEV distribution fails to explain the dispersion above the median, which is significantly higher for the observed data. Also, for the last bin, and to some extent also for the fourth one, the spread of the data under the median can not be explained just by random sampling from GEV distributions.

3.4 Discussion

Even though the results of the Monte Carlo simulations clearly point out that selecting the GEV distribution as a pan-European parent cannot fully describe the observed variability of sample L-moments, there are some aspects that deserve a deeper dis-

- ¹⁵ cussion. In fact, it is remarkable that for all considered European geographical areas, including catchments with very different sizes, climatic conditions, and geomorphologic characteristics covered in the FloodFreq database, there is not enough statistical evidence to reject the hypothesis that the GEV distribution is a suitable parent distribution for describing the median behaviour in terms of sample L-moment ratios. From
- ²⁰ a purely statistical point of view, this could be explained by the fact that the GEV distribution is the theoretical extreme value distribution that expresses in a closed analytical way the three possible asymptotic distributions derived from any kind of parent population, as described in the Fisher–Tippett–Gnedenko theorem (Fisher and Tippett, 1928; Gnedenko, 1943). Therefore, it offers a theoretical justification for using it to reproduce
- the sample frequency distribution of annual maxima series from many different hydrological and geological extreme phenomena (precipitation depths, flood flows, earthquake magnitudes, wind-speeds and other) observed in different geographical contexts



around the world (e.g. Robson and Reed, 1999; Castellarin et al., 2001; Thompson et al., 2007; Grimaldi et al., 2011).

Nevertheless, the results for the Monte Carlo simulations regarding the spread of the L-moment ratios around the GEV line show that the dispersion is bigger than expected

- from random sampling, particularly for the deviations above the median. In the terminology used by Matalas et al. (1975), a "kurtosis separation" appears, if only the GEV distribution is considered as the underlying parent across Europe. Inter-site correlation is most probably present in the original annual flood flow series, from which the sample L-moment ratios have been computed, and this correlation should reduce the observed
- ¹⁰ L-moments variability. In the Monte Carlo generations, this inter-correlation it has been entirely neglected and still, the variability of the generated L-moments is lower than the observed one. Also, sample estimation uncertainty, particularly for high values of L-*Ck*, could also play a role by augmenting the variability in the observed L-moments, but the systematic underestimation of the dispersion points out to the fact that the GEV distri-
- ¹⁵ bution alone is not complex enough to fully describe the variability of sample L-*Cs* and L-*Ck* values estimated for the FloodFreq database, being these L-moment ratios surrogates for the entire spectrum of flood generation processes occurring across Europe responsible for the diversity of shapes of flood frequency distributions. It is therefore necessary to further investigate the links of hydrological processes to the L-moment
- ratios, and in particular to high values of skewness and kurtosis, in order to try to explain these discrepancies. The next section focuses precisely on defining the controls of catchment and climate indicators on the averaged L-moment ratios and the regional flood frequency distributions.





4 Catchment and climate controls on regional flood frequency

4.1 Description of the dataset

The analysis presented in this section focuses on annual maximum series (AMS) of peak flow from three national databases, namely Austrian, Italian and Slovakian, and

⁵ it addresses the control of catchment size and climate, respectively, on the flood frequency regime. In particular, the analysis considers catchment area and mean annual precipitation (MAP) as catchment descriptors for the three datasets. Both indices are, after the FloodFreq survey, easily available across all European countries and are commonly used in practice. Also, previous studies have proven them to exert significant
 ¹⁰ control on the frequency regime of hydrological extremes (see e.g. Schaefer, 1990; Blöschl and Sivapalan, 1997; Brath et al., 2003; Di Baldassarre et al., 2006; Padi et al., 2011).

When combined, the three national datasets consist of AMS from a total of 1132 catchments (Austria, 676 gauges; Italy, 282 gauges and Slovakia, 174 gauges). Sam-¹⁵ ple values of L-*Cs* and L-*Ck* estimated from this subset are represented with dark grey rings in Fig. 1a, which shows that the new subset spans the original spectrum in terms of L-moment ratios of the entire FloodFreq database. Table 3 describes the dataset in terms of: catchment area, mean annual precipitation (MAP), record length of annual maximum series (*n*) and sample L-*Cv*, L-*Cs* and L-*Ck* for the case study.

²⁰ The geographical locations of the considered streamgauges are shown on the map in Fig. 2.

As illustrated in the scatterplot of Fig. 3, the dataset includes a range of values for catchment area and MAP, and does not show any statistically significant correlation between the two (i.e. sample Pearson coefficient is equal to -0.010, and the null hy-

²⁵ pothesis of zero correlation is associated with a *p* value of 0.732). It is worth noting here that, as illustrated in Fig. 3, very large catchments (catchment areas larger than 10 000 km²) are associated with medium MAP values (about 1200 mm yr⁻¹). Therefore, very large catchments in the study area are neither wet nor dry catchments ("wet"



and "dry" as defined in Sect. 4.2), and this is an important element for the analyses described in Sects. 4.2 and 4.3.

4.2 Area and MAP control on sample L-moments

A more detailed exploration was undertaken to better understand the controls on the flood frequency regime exerted by physiographic and climatological factors, represented here by area and MAP. To minimize the possible effects of sampling variability associated with short records when estimating higher order sample L-moments (see e.g. Viglione, 2010), the minimum record length was set to 25 yr of data, reducing the dataset to a total of 813 catchments (Austria, 493 gauges; Italy, 151 gauges and Slovakia, 169 gauges). The combined dataset was divided into six smaller subsets based on thresholds defined as the 20 and 80 % quantiles of the catchment descriptor values. For convenience, the following subsets are defined to characterise the catchments according to size: small catchments (area < 55 km²), intermediate catchments (55 km² < area < 730 km²) and large catchments (area > 730 km²).

- ¹⁵ Analogously, the catchments were classified based on MAP as: dry catchments (MAP < 860 mm yr⁻¹), medium catchments (860 mm yr⁻¹ < MAP < 1420 mm yr⁻¹) and wet catchments (MAP > 1420 mm yr⁻¹) (see also Fig. 3). The adjectives dry and wet, and small and large are relative to the distribution of wetness and sizes of the study dataset. The 20 and 80 % quantiles were selected after a set of preliminary trials as
- they enabled to enhance the representation of the peculiarities in the flood frequency regimes for drier against wetter and for larger against smaller catchments for the considered dataset.

For each of the wetness and size subsets, the record length weighted moving average (WMA) values of sample L-Cv, L-Cs and L-Ck was computed using a window of 70 catchments, where the 70 neighbouring catchments were selected by taking the

of 70 catchments, where the 70 neighbouring catchments were selected by taking the closest catchments in terms of the considered descriptor (area or MAP). For each 70 catchments sample, the associated WMA value was plotted against the corresponding mean of catchment descriptor (area or MAP) as shown in Fig. 4 for each of the six



subsets. Note that each individual WMA value has a regional validity, as it is derived from a pooling-group of 70 sites, defined based on the similarity in terms of catchment size and rainfall regime (MAP). For example, the first point of the yellow line in Fig. 4a represents a non-contiguous region with MAP < 860 mm yr^{-1} (dry catchments) and the

- ⁵ 70 smallest sizes of the subset (in this case, catchment areas from 36 to 103 km^2). The minimum amount of information for each point, assuming serial and spatial independence of the stations, would correspond to $70 \times 25 = 1750$ station-years of data. The width of the window (i.e. 70 sites) provides a trade-off between the desire to effectively identify and visualise large-scale structures in the dataset and local deviations from the averaging process, and the conflicting need to work on large samples to reduce the
- effects of sampling uncertainty.

Considering the WMA values plotted in Fig. 4, an observable feature is a general tendency for all the L-moment ratios to decrease with increasing area and MAP values. This is a result already reported in the literature for the case of conventional product

- ¹⁵ moments, with special focus on scale effect on the coefficient of variation of the flood distribution (see e.g. Schaefer, 1990; Blöschl and Sivapalan, 1997; Brath et al., 2003; Merz and Blöschl, 2003, 2009; Di Baldassarre et al., 2006; Padi et al., 2011; Viglione et al., 2012). The largest gradients are observed for L-*Cv*, followed by L-*Cs* and, finally, L-*Ck*, confirming the lower variability of higher order L-moments in space (see e.g.
- Hosking and Wallis, 1997), and also showing that the lower order L-moment ratios have a stronger link to catchment and climate properties than higher order L-moment ratios. It is also noticeable that the WMA lines are not evenly spaced, which indicates a degree of non-linearity between the flood characteristics and the catchment properties. This is particularly evident when considering L-Cv plotted against both catchment area and
- MAP on Fig. 4a and b, for L-Cs plotted against MAP (subsets defined based on area) on Fig. 4d, and, to some extent, for L-Ck plotted against MAP (again, subsets defined based on area) on Fig. 4f.





4.3 Area and MAP control on regional flood frequency distribution

Acknowledging the influence of both catchment size and mean annual precipitation on the L-moment ratios, the next step in the analysis is to assess the impact of this influence on the underlying regional parent distribution of annual flood sequences. This investigation is based on the novel use of L-moment ratio diagrams, which, in this con-5 text, are used to analyse the sensitivity of the choice of a parent distribution to the catchment and climate characteristics. The two types of the L-moment ratio diagram described in Sect. 3.1 were used: (i) L-Cv - L-Cs diagram and (ii) L-Cs - L-Ck diagram. The former is used in this study for assessing the suitability of the commonly used 2-parameter distributions Gumbel (GUM), Gamma (GAM), 2-parameter Lognor-10 mal (LN2) and Exponential (EXP), while the latter is used in connection with the 3parameter distributions that were previously recalled (i.e. GLO, GEV, LN3 and PE3). The assessment of which statistical model fits better the averaged statistical properties of the sample was done visually based on the distance between the averaged sample L-moment ratios and the theoretical lines, as objective goodness of fit measures

¹⁵ ple L-moment ratios and the theoretical lines, as objective goodness of fit measures require the flood peak data (see e.g. Laio, 2004), and in this case only the L-moment ratios were available.

The diagrams in Fig. 5 report the WMA values of L-*Cs* and L-*Cv* associated with a given average value of catchment area or MAP for the same 70 catchments moving windows defined in the previous section and shown in Fig. 4, again stratified in small, intermediate and large catchments (Fig. 5a) and wet, medium and dry catchments (Fig. 5b). To emphasize the influence of the catchment descriptors (i.e. area or MAP), the colour intensity of each plotted WMA value has been graded according to the value of the catchment descriptor that has not been used for the stratification, with increasing intensity for increasing descriptor value. For example, Fig. 5a shows the WMA values when the dataset is divided by catchment size into small, intermediate and

large catchments, and the colour grading of the points reflects the mean value of MAP for each 70 catchments subset. More precisely, red WMA values of L-Cv and L-Cs





in Fig. 5a correspond to the transect associated with small basins in the catchment descriptor space defined by MAP, orange relates to the intermediate size basins transect in the catchment descriptor space defined by MAP and brown points stand for the large basins transect in the catchment descriptor space defined by MAP. Analogously,

- in Fig. 5b, yellow WMA values of L-Cv and L-Cs represent the transect associated with dry basins in the catchment descriptor space defined by catchment area, green corresponds to the medium MAP basins transect in the catchment descriptor space defined by area, and blue points relate to the wet basins transect in the catchment descriptor space defined by area.
- ¹⁰ The position of the WMA values of sample L-*Cv* and L-*Cs* relative to the theoretical distributions shown in Fig. 5a and b indicate that none of the considered 2-parameter distributions fits the statistical properties of the datasets. In particular, both figures show that the WMA values of sample L-*Cs* are always larger than that of the *Gumbel* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distribution (fixed value of 0.1699) and smaller than that of the *Exponential* distributio
- value of 0.3333), with the exception of values up to 0.36 for the smallest dry (low MAP) catchments (less intense yellow points in Fig. 5a). Sample values of L-moment ratios do not seem follow systematically the shape of any of the lines representing the theoretical L-*Cv* and L-*Cs* relationships of the considered 2-parameter distributions, but some WMA values tend to lie closer to the LN2 curve than to any other. This is the case
- ²⁰ for the intermediate sized and medium MAP catchments of the dataset (mid-intensity orange and mid-intensity green points in Fig. 5a and b, respectively). The only subset, for which sample values approach the statistical properties of the *Gumbel* distribution, and they do it towards the intersection with the LN2 curve, is for large medium MAP catchments (intense green points in Fig. 5b and, to some extent, mid-intensity brown
- ²⁵ points in Fig. 5a). The subset corresponding to dry catchments presents the largest L-*Cv* and L-*Cs* values, while the smallest L-moment ratios are found for the subset of large catchments, lying as mentioned before closer to the *Gumbel* line than the rest of WMA values. Inside each subset (i.e. small, intermediate, large, dry, medium or wet basins) the intensity of gradation increases with decreasing L-*Cv* and L-*Cs* values.



This means that for larger values of catchment area and MAP, lower regional averaged values of L-Cv and L-Cs are expected. The gradients are clearer for the small and dry catchments (red and yellow points in Fig. 5), while there is a slight increase of the WMA L-Cs values for wetter catchments inside the large catchtments subset. This

- ⁵ could be attributed to the fact that, as pointed out in Sect. 4.1, large catchments have all a similar averaged MAP value (between 1000–1400 mm yr⁻¹) belonging to the same intermediate wetness subset and the differences in rainfall regime are not big enough to draw conclusions about their control on the averaged L-*Cs* values inside the group. Figures 6 and 7 report the L-moment diagrams defined by plotting WMA values of L-
- Figures 6 and 7 report the L-moment diagrams defined by plotting WMA values of L *Cs* and L-*Ck* in a similar fashion to Fig. 5. In this case, the two intermediate subsets (i.e intermediate size and medium MAP values) were plotted separately from the subsets defining small, large, dry and wet catchments to ease the visual interpretation of the plots (as far as possible avoiding overlapping points). Figure 6a shows the subset of WMA values derived for the small and large catchments, with the colour intensity rep resenting the average MAP value and Fig. 6b illustrates intermediate size catchments
- with the gradation representing again the average MAP value. Similarly, Fig. 7a shows the subset of WMA values representing dry and wet catchments, with the colour intensity representing catchment size, while Fig. 7b is relative to the subset characterized by intermediate MAP values.
- Figure 6a shows that the WMA values associated with large catchments are located closer to the GEV line than to any other distribution, generally showing slightly higher L-*Ck* values than expected for a GEV distribution. For small catchments, the GEV is the distribution that best represents the statistical properties of sample, being the scatter of points much closer to the theoretical curve than for the subset of large catchments.
- ²⁵ For intermediate-sized catchments, Fig. 6b highlights a strong control of MAP on the appropriate distribution; medium-sized catchments associated with high MAP values are situated closer the curve of the GEV distribution, while catchments with lower MAP values move towards the LN3 distribution. This implies that, for drier catchments inside





the intermediate-sized subset, the distribution type shifts to a more skewed one (for the same L-*Ck*, the LN3 has higher L-*Cs* values than GEV).

Figure 7a shows the WMA values for the two subsets including the most dry and wet catchments as defined by the MAP values. The WMA values associated with wet so catchments are located closer to the line defining the GEV distribution, suggesting

- that GEV is an appropriate distribution for wet catchments more or less regardless of catchment size (as determined by the blue colour gradation). In contrast, the statistical properties of the dry catchments are better represented by the LN3 distribution, as also illustrated by Fig. 6b. Catchments with intermediate MAP values are associated with
- ¹⁰ a larger range of L-*Cs* values depending on their size (see Fig. 7b), and lie closer to the GEV line than to any other distribution considered, with a slight tendency for the smallest and largest catchments inside the subset to exhibit higher values of L-*Ck* than expected from a GEV distribution.

Analogously to Fig. 5, the area and MAP control on the position of the relative WMA values between the subsets remain in Figs. 6 and 7, showing again higher averaged L-moment ratio values when comparing small to large catchments and dry to wet catchments.

4.4 Discussion

Section 3 has highlighted the importance of linking the flood generation processes to

- the observed L-moment ratios of the annual maxima sequences, and the position of the regional averages at the diagrams, in order to understand from the differences between catchments in terms of underlying parent distributions. In Sect. 4, two lumped catchment descriptors are used as surrogate covariates representing the spatially distributed and complex hydrological processes controlling the catchment flood response. Pre-
- cisely, the area of the basin is an indicator of the scale interplays between catchment processes and rainfall (Blöschl and Sivapalan, 1995), while mean annual precipitation acts as control of probabilistic behaviour of floods through its effect on antecedent soil





moisture conditions (Sivapalan et al., 2005), and also provides an indication on other local and atmospheric process.

For example, low MAP values could indicate regions with prevalence for more localised and variable storms, usually flashier in time and with higher rainfall intensities.

- ⁵ This higher between-years variability and skewed distribution of rainfall extreme intensities translates into higher L-*Cv* and L-*Cs* values of annual floods, as Figs. 5b and 7a suggest. In contrast, long duration frontal or advective events, associated with larger spatial extensions and lower rainfall intensities, are expected at catchments presenting higher MAP values, more clearly shown in Fig. 7a. These two kinds of precipitation regimes, will also have an effect on the co-evolution of the catchment geology (Gaál
- regimes, will also have an effect on the co-evolution of the catchment geology (Gaal et al., 2012), in which rainfall plays an important role at multiple time scales. The variability of flood magnitude between years, and the L-coefficient of variation as a measure of this variability, tends to be higher in small and intermediate-sized catchments, compared to the larger ones, as shown in Fig. 7. The main reasons are both the spatial
- heterogeneity of rainfall and the interaction between the spatial and temporal scales of rainfall and catchment size taking place. This interplay causes the catchment to resonate with storms of similar spatio-temporal extension. In the case of small basins this corresponds to short duration, high intensity, spatially concentrated storms (i.e. convective events or flash floods), which are also typical of drier climates; while in
- ²⁰ large catchments the resonance appears with longer storms, usually associated with lower intensities, with a bigger spatial extension (i.e. advective or frontal events), more typical of wetter environments (see e.g. Blöschl and Sivapalan, 1995; Sivapalan and Blöschl, 1998). These two differentiated regimes for rainfall extremes will cause not only a higher L-coefficient of variation but also a higher L-coefficient of skewness in the
- flood distributions for smaller and drier catchments compared to the larger and wetter ones, as shown in Fig. 6a. Aside from precipitation input, other catchment processes can also play an important role in shaping the properties of the flood distribution. The presence of non-linearities in runoff production and routing in small, dry basins (Medici et al., 2008) in contrast to the aggregation of processes in larger catchments (Sivapalan





et al., 2002) will translate in decreasing values of L-*Cv* and L-*Cs* with increasing values of MAP and, more strongly, catchment size. One visible consequence of the higher dispersion and skewness of the flood frequency distributions with decreasing catchment area and increasing aridity is the fact that predicting flood magnitudes and exceedance probabilities in ungauged basins is more difficult in smaller, more arid catchments, as compared to bigger, less arid ones (see e.g. Salinas et al., 2013).

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Therefore, the main findings from the analysis presented in the previous sections need to be interpreted in a hydrological way, instead of in a merely statistical sense. For example, the fact that the GEV distribution is found to be the model representing better the everaged statistical preparties of establishments with medium to high values of

- better the averaged statistical properties of catchments with medium to high values of MAP regardless of size, is probably because few of the catchments in arid regions with highly skewed distributions of rainfall extremes are present in these sub-classes. In contrast, there is a clear indication that the LN3 distribution, which has a higher skewness than GEV for a given kurtosis, reproduces better the sample properties of the dry,
- intermediate-sized subset, representing most likely other flood generation processes than for the data subsets more affine to the GEV distribution. Nevertheless, the limited number of catchments classified simultaneously as small and dry, large and wet, or large and dry prevents these conclusions to be extended further.

The LN2 distribution represents in some circumstances a valid alternative to the other commonly used 3-parameter distributions, especially for intermediate-sized, medium MAP catchments. The fact of having one parameter less than the GEV or the LN3, allows the LN2 to reproduce a only limited range of hydrological processes maybe not able to capture the extreme cases of the smaller or drier catchments. Sample L-*Cs* values are shown to be, on regional average, higher than the one of the *Gumbel* distribution, being the large, medium MAP catchments the ones closer to its theoretical curve. This is likely due to the fixed skewness value of the *Gumbel* distribution,

relatively low for the regional averages of the given dataset and the selected aggregation levels, corresponding substantially to the smoother processes in larger catchments. Also, for the small, wet and dry catchments, sub-classes none of the considered





2-parameter distributions is capable of accurately represent the averaged values of the subset.

The novel use of traditional L-moment ratio diagrams presented in Figs. 5, 6 and 7 may be very informative, and could help to better understand the changes in flood haz-⁵ ard resulting from different sources of environmental change. By explicitly accounting for the conceptual process controls through catchment descriptors (catchment area and MAP in this study), the sensitivity of the flood frequency distribution to changes in process controls can be determined. For example, Figs. 6b and 7a show that for

medium-sized catchments the most appropriate distribution changes from a GEV to
 a LN3 distribution as MAP reduces. Thus, if future climate projections indicate a reduction of MAP, then the results in Figs. 6b and 7a suggest that the corresponding change in flood distribution is likely to be characterised by a move towards a larger skewness (e.g. from a GEV to a LN3 distribution), assuming that the current relationship between MAP and storm rainfall intensity distributions holds in future climates. This sensitivity analysis could be extended by including additional catchment descriptors representing processes likely to change, e.g. land cover and urbanisation, but also to weight each distribution type in case a multi-model approach is selected for representing the regional flood frequency distribution (see e.g. Laio et al., 2009).

5 Conclusions

The issue of existence of underlying parent flood frequency distributions across different processes, places and scales is directly addressed in this study. One of the mostly applied and recommended statistical models, the GEV distribution, has proven to capture the mean and median statistical properties of a pan-European database annual maximum flood series, but the observed variability in the data is larger than what this model can randomly reproduce. This implies that the GEV alone can not be considered as a candidate for a pan-European flood frequency distribution, as it is not



complex enough to reproduce the entire variety of hydrological processes leading to the different shapes of flood frequency curves.

There are many examples that show that one single analytic expression across large scales and more important, across different processes, is not valid for describing all possible local characteristics at once. Rogger et al. (2012) proved that step changes appear in the flood frequency curve when local runoff generation mechanisms are influenced by threshold processes, especially for small mountainous catchments, and these are not captured by any traditional statistical model so far. The case of several

- Mediterranean regions which are characterized by two distinct flood populations is also very usual. These populations are referred by Rossi et al. (1984) as "ordinary floods", generated by frontal-type rainfalls, and "extraordinary floods", generated by highly convective rainstorms. For the modelling of these flood regimes it could be appropriate to use the TCEV model (see e.g. Francés, 1998), as there is a mixture of populations, while it could be wrong to apply it in other regional contexts if there there is not such
- ¹⁵ a mixing. Merz and Blöschl (2003) showed for an Austrian dataset that different typologies of floods classified after their generation mechanisms may have very different statistical properties and can therefore lead to distinct flood frequency distributions. In particular, if many flood generation processes take place in one catchment, possible depending on rainfall or snowfall regimes, the overall flood frequency distribution is
- ²⁰ a result of the combination of the distributions associated to the single mechanisms and is not necessarily expressed in terms of a single analytical model.

The inclusion of information on the underlying hydrological processes in the model choice is therefore of high importance. In this study, each catchment is characterized in terms of size and mean annual precipitation, as these properties have previously been

found to be rough surrogates for the different flood generation processes, but also because the FloodFreq survey showed that only these, the most elemental catchment properties, are readily available across Europe. Several studies of flood hydrology have also highlighted the potential utility of soil and land-use data for characterizing flood frequency curves in ungauged European catchments. Thus, there are potentially large





benefits associated with future development of consistent pan-European catchment descriptor datasets as a fundamental step in harmonizing methods.

The original utilization of the traditional L-moment ratio diagrams presented in this study, in conjunction with a more refined characterization of European catchments ⁵ based upon a richer catchment descriptor dataset could contribute to better understand the modifications in flood hazard resulting from different sources of environmental change, and to move further steps towards the definition of a set "process driven" pan-European flood frequency distributions.

Acknowledgements. The authors are grateful for the financial contribution made by the COST
 Office grant ES0901 "European procedures for flood frequency estimation (FloodFreq)" and for contributions made by members of Working Group 2 of the COST Action. Funding from the ERC *FloodChange* project (ERC Advanced Grant FP7-IDEAS-ERC-AG-PE10 291152) and from the Austrian Science Funds (FWF) as part of the Vienna Doctoral Programme on Water Resource Systems (*DK-plus* W1219-N22) is also acknowledged. The compilation of the

Italian dataset was partially supported by the Italian Government through its national grant to the programme on "Characterisation of Ungauged Basins by Integrated uSe of hydrological Techniques" (CUBIST Project) and the compilation of the Slovakian dataset was partially supported by the Agency for Research and Developement under contract No. APVV-0496-10. Both supports are greatly acknowledged. Juraj Parajka is thankfully acknowledged for preparing the man in Fig. 2 as well as Günter Blöschl for his constructive comments and suggestions.

²⁰ map in Fig. 2, as well as Günter Blöschl for his constructive comments and suggestions.

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Table 1. FloodFreq streamflow database: number of sites and station-years of data for the national annual maxima sequences.

Country	No. of sites	Station-years of data	Kind of data
Austria	676	28 592	Instantaneous
Cyprus	9	382	Daily
Germany	415	22 5 1 6	Daily
Denmark	43	2789	Daily
France	1172	45 331	Instantaneous
Ireland	215	6708	Instantaneous
Italy	373	8207	Instantaneous
Lithuania	30	1953	Instantaneous
Norway	104	3120	Daily
Poland	39	3426	Instantaneous
Slovakia	174	7995	Instantaneous
Spain	220	8594	Instantaneous
United Kindom	635	23 200	Instantaneous
FloodFreq	4105	162813	

Table 2. Empirical p values for the observed quantiles of L-Ck given the sample distributions
generated from the GEV simulations shown in Fig. 1b. In bold, values passing a 5 % significance
test.

	Range of L- <i>Cs</i> values					
L- <i>Ck</i> quantile	0–0.11	0.11–0.22	0.22-0.33	0.33–0.44	0.44–0.55	
90 %	0.999	0.999	1.000	1.000	1.000	
70%	0.990	0.997	0.997	0.992	0.963	
50 %	0.841	0.872	0.688	0.972	0.067	
30 %	0.279	0.607	0.133	0.793	0.004	
10%	0.095	0.289	0.029	0.016	0.000	





Table 3. Summary of the Austrian, Italian and Slovakian national datasets. Information on the
distribution of catchment area, mean annual precipitation (MAP), record length (n) and sample
L-moment ratios of the annual flood sequences is given.

	Area	MAP	п	L- <i>Cv</i>	L- <i>Cs</i>	L- <i>Ck</i>
	(km²)	$(mm yr^{-1})$	(yr)	(—)	(—)	(—)
Min.	4.6	501.7	9	0.0152	-0.1209	-0.1583
1st Quartile	64.9	902.8	22	0.2194	0.1777	0.1268
Median	157.0	1112.0	34	0.2763	0.2705	0.1905
Mean	2096.5	1163.6	38	0.2945	0.2782	0.2074
3rd Quartile	534.0	1369.3	47	0.3558	0.3733	0.2730
Max.	131 488.0	2312.3	182	0.7691	0.7737	0.7132







Fig. 1. (a) L-*Cs* – L-*Ck* diagram for the FloodFreq database with the record length weighted moving average over 200 catchments (purple line) and the theoretical relationships between L-*Cs* and L-*Ck* for several distributions. **(b)** Monte Carlo simulations results for 50 000 generated GEV Europes.





Fig. 2. Map showing the location of the 1132 considered Austrian, Italian and Slovakian gauging stations (points). Color scale in the background represents terrain elevation in m.a.s.l. (above sea level).





Fig. 3. Catchment characteristics of the Austrian, Slovakian and Italian datasets. For each catchment, mean annual precipitation (MAP) is plotted against catchment area (grey circles). Black dashed lines represent the 20 and 80 % quantiles for each catchment descriptor, defining the subsets small (area < 55 km^2), intermediate (55 km^2 < area < 730 km^2), large (area > 730 km^2), dry (MAP < 860 mm yr^{-1}), medium ($860 \text{ mm yr}^{-1} < \text{MAP} < 1420 \text{ mm yr}^{-1}$), and wet catchments (MAP > 1420 mm yr^{-1}).





Fig. 4. Sample L-*Cv*, L-*Cs* and L-*Ck* values for each catchment (grey points) plotted against catchment area and mean annual precipitation (MAP). Lines show the record length weighted moving averages (WMAs) over 70 catchments for the subsets small, intermediate, large, dry, medium, and wet defined in Fig. 3.













Fig. 6. L-moment ratio diagrams for the subsets defined by catchment area: (a) small, large, and (b) intermediate described in Fig. 3. Each point represents the record length weighted moving average (WMA) over 70 catchments of L-coefficient of kurtosis (L-Ck) against corresponding values of L-coefficient of skewness (L-Cs) and the color intensity is proportional to mean annual precipitation (MAP).





Fig. 7. L-moment ratio diagrams for the subsets defined by mean annual precipitation, MAP: (a) dry, wet, and (b) medium described in Fig. 3. Each point represents the record length weighted moving average (WMA) over 70 catchments of L-coefficient of kurtosis (L-Ck) against corresponding values of L-coefficient of skewness (L-Cs) and the color intensity is proportional to catchment area.



Discussion Paper

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