# Highlights

**Extreme Precipitation Return Levels for Multiple Durations on a Global Scale**

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- Global precipitation return levels for 3-hour to 10-day durations are analysed
- Three different extreme value distributions are used to estimate the extremes
- The MEV distribution shows the most coherent spatiotemporal patterns
- Two distributions show a global shift from heavy to thin tails for longer durations

# Extreme Precipitation Return Levels for Multiple Durations on a Global Scale

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**Abstract**

Quantifying the magnitude and frequency of extreme precipitation events is key in translating climate observations to planning and engineering design. Past efforts have mostly focused on the estimation of daily extremes using gauge observations. Recent development of high-resolution global precipitation products, now allow estimation of global extremes. This research aims to quantitatively characterize the spatiotemporal behavior of precipitation extremes, by calculating extreme precipitation return levels for multiple durations on the global domain using the Multi-Source Weighted-Ensemble Precipitation (MSWEP) dataset. Both classical and novel extreme value distributions are used to provide an insight into the spatial patterns of precipitation extremes. Our results show that the traditional Generalized Extreme Value (GEV) distribution and Peak-Over-Threshold (POT) methods,

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which only use the largest events to estimate precipitation extremes, are not spatially coherent. The recently developed Metastatistical Extreme Value (MEV) distribution, that includes all precipitation events, leads to smoother spatial patterns of local extremes. While the GEV and POT methods predict a consistent shift from heavy to thin tails with increasing duration, the heaviness of the tail obtained with MEV was relatively unaffected by the precipitation duration. The generated extreme precipitation return levels and corresponding parameters are provided as the Global Precipitation EXtremes (GPEX) dataset. These data can be useful for studying the underlying physical processes causing the spatiotemporal variations of the heaviness of extreme precipitation distributions.

*Keywords:* Precipitation extremes, MSWEP, Metastatistical extreme value distribution, Generalized extreme value distribution, Peaks-over-threshold, Global domain
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## 1. Introduction

Extreme precipitation events are a major contributor to natural disasters (CRED, 2019). Accurate estimates of the severity of intense precipitation events are needed for an enhanced disaster risk understanding, such as that of floods and landslides. The urgency of this is indicated as the first priority of the Sendai Framework for Disaster Risk Reduction (UNSIDR, 2015). The accurate quantification of extremes is also necessary for infrastructure planning and design. Some countries already provide spatiotemporal estimates of extreme precipitation based on extreme value distributions (EVDs), for example, for Australia (Ball et al., 2019), the Netherlands (Beersma et al., 2018), and the US (e.g., Perica et al., 2015, 2018). However, many countries and regions do not have sufficient local data available (Gründemann et al., 2018; Kidd et al., 2017; van de Giesen et al., 2014), such that spatially-distributed extreme precipitation estimates are not possible.

Several previous studies have developed global-scale datasets of extreme precipitation. Courty et al. (2019) calculated intensity-duration-frequency curves at the global domain and their scaling with different event durations using reanalysis data and the Generalized Extreme Value (GEV) distribution with fixed tail behavior. Donat et al. (2013) produced the HadEx-2

dataset, which contains 29 generic precipitation and temperature indices, although these indices are not based on EVDs. Furthermore, this dataset has a coarse 2.50° latitudinal × 3.75° longitudinal resolution, with data-gaps due to insufficient available gauge data. Other global studies mostly focused on examining which type of distribution is most suitable to capture the tail behavior of extreme precipitation (Cavanaugh and Gershunov, 2015; Cavanaugh et al., 2015; Papalexiou et al., 2013). In addition, the spatial patterns of the parameter controlling the tail decay have been studied for the GEV distribution (Papalexiou and Koutsoyiannis, 2013; Ragulina and Reitan, 2017), and the Generalized Pareto (GP) distribution (Serinaldi and Kilsby, 2014). However, several issues remain to be addressed in order to obtain global-domain extreme precipitation return levels: 1) the choice of the dataset, 2) the focus on daily durations, 3) the choice of the time blocks over which block-maxima are determined, and 4) the exploration of possible alternatives to the classical EVDs and the associated uncertainty with respect to the tail behavior.

1. Several (quasi-)global gridded precipitation datasets have been developed in the recent years, each with strengths and weaknesses. See Sun et al. (2018) and Beck et al. (2019a) for recent overviews of available datasets. Most of these datasets are based on gauge, reanalysis, or satellite sensor data. Notable examples of gauge-based datasets include GPCC-FDR (Becker et al., 2013; Schneider et al., 2011) and REGEN (Contractor et al., 2020). However, gauges are extremely unevenly distributed across the globe (Kidd et al., 2017; Schneider et al., 2014), and the number of active gauges has been declining in recent decades (Mishra and Coulibaly, 2009). Satellite-based products such as CMORPH (Joyce et al., 2004), GSMaP (Ushio et al., 2009), IMERG (Huffman et al., 2015), and PERSIANN (Hong et al., 2004) have a relatively high spatio-temporal resolution. However, they do not cover regions outside of 60°N/S, and are only available from 2000 onwards, which significantly hinders their use for extreme value analyses. Precipitation products with a true global coverage and long records are reanalyses, such as ERA-5 (Hersbach et al., 2020), JRA-55 (Kobayashi et al., 2015), and MERRA-2 (Gelaro et al., 2017). However, reanalysis products tend to exhibit strong systematic biases in the magnitude and frequency of precipitation (Decker et al., 2012; Liu et al., 2018; Ménégoz et al., 2013).

2. Global-scale analyses of precipitation extremes are generally based on daily precipitation records (Cavanaugh et al., 2015; Koutsoyiannis, 2004a,b; Papalexiou and Koutsoyiannis, 2013; Papalexiou et al., 2013; Ragulina and Reitan, 2017; Serinaldi and Kilsby, 2014). In practice, however, multiple durations are needed for the design of infrastructure (e.g., Nissen and Ulbrich, 2017) or urban drainage networks (e.g., Mailhot and Duchesne, 2009). It is known that precipitation extremes of different durations scale differently with temperature (Wasko et al., 2015), but little is known about the variation of EVD properties (tail behavior) for different temporal resolutions. Studies that did derive extreme precipitation statistics for durations ranging from minutes to a few days have mostly focused on small regions (McGraw et al., 2019; Nissen and Ulbrich, 2017; Overeem et al., 2008).
3. Studies estimating return levels of extreme precipitation by using annual maxima typically use calendar years to delineate the annual periods from which maxima values are extracted (e.g., De Paola et al., 2018; Marani and Zanetti, 2015; Papalexiou and Koutsoyiannis, 2013; Ragulina and Reitan, 2017; Villarini et al., 2011). When the variable of interest is river discharge instead of precipitation, however, hydrological years are typically used instead of calendar years to determine the annual maxima (Ward et al., 2016). For discharge values this is important, since peak discharge and flooding could occur during 31 December to 1 January transition and one event would be included in two calendar years. Although not often considered, this could also happen for precipitation. The annual maxima method could pick multiple values from a single rainy season that may, for example, be highly influenced by the El Niño-/Southern Oscillation, which is known to impact precipitation extremes (Allan and Soden, 2008; Rasmusson and Arkin, 1993).
4. The Generalized Extreme Value (GEV) distribution, the most widely used EVD, is typically fitted through one of two approaches: a) using annual maximum precipitation series and maximum likelihood (Coles, 2001) or L-moment (Hosking, 1990) estimation approaches, or b) using a Peak-Over-Threshold (POT) method to fit a Generalized Pareto Distribution to excesses above the threshold and a Poisson process to the sequence of threshold exceedances (Coles, 2001). In contrast to GEV and POT, the recently developed Metastatistical Extreme Value (MEV) distribution is fitted using all events with recorded precipita-

tion instead of only the most severe. The inclusion of more events reduces the uncertainty due to sampling effects, which is important when dealing with short time series (Hu et al., 2020; Marani and Ignaccolo, 2015; Marra et al., 2018, 2019a; Miniussi and Marani, 2020; Zorzetto et al., 2016; Zorzetto and Marani, 2019). This is particularly advantageous when analyzing short remote sensing precipitation products, as the commonly applied GEV requires many years of data to accurately estimate the tail of the distribution (Papalexiou and Koutsoyiannis, 2013). Additionally, GEV parameter estimation depends heavily on a few large values, which makes it very sensitive to the possible presence of outliers, a relatively common occurrence in remote sensing estimates of precipitation amounts (Zorzetto and Marani, 2020). The GEV tail behavior is mostly controlled by its shape parameter, which is very sensitive to sampling effects and the choice of the method used for estimation. To overcome these problems, some studies have suggested to use one universal value of the shape parameter that is applicable to the whole world Koutsoyiannis (2004a,b), or a shape parameter value within a narrow range between exponential and heavy-tail behavior (Papalexiou and Koutsoyiannis, 2013), or one shape parameter per region, that is similar within climate types and elevation ranges (Ragulina and Reitan, 2017). The estimation of the shape parameter is particularly difficult with short data series, though crucial for the accurate estimation of extremes.

In this study we contribute to overcome these issues by 1) using a dataset that merges all three main sources of precipitation data, 2) estimating extremes for several event durations, 3) using hydrological years in our analyses, and 4) comparing results from three different extreme value methods (GEV, POT and MEV). Specifically, we are interested in quantitatively characterizing the behavior of extreme precipitation and the spatiotemporal variation of extreme value distributional tails at the global domain.

## 2. Material and Methods

### *2.1. Data*

The global precipitation product used in this study is the Multi-Source Weighted-Ensemble Precipitation (MSWEP-V2.2) dataset. MSWEP is particularly suited for our purpose due to its global coverage, long temporal

span, high spatial and temporal resolution. We used data from 1 January 1979 to 31 October 2017 at a 0.1° latitude × 0.1° longitude resolution at 3-hourly time steps. We selected all land-cells between 90°N and 58°S for our analysis. MSWEP precipitation estimates are derived by merging five different satellite- and reanalysis-based global precipitation datasets. The dataset is one of the few precipitation products with daily (as opposed to monthly) gauge corrections, applied using a scheme that accounts for gauge reporting times (Beck et al., 2019b). MSWEP has shown robust performance compared to other widely used precipitation datasets (e.g., Alijanian et al., 2017; Bai and Liu, 2018; Beck et al., 2017, 2019a; Casson et al., 2018; Hu et al., 2020; Sahlu et al., 2017; Satgé et al., 2019; Zhang et al., 2019), thus underlying its potential for improving the characterization of extreme precipitation worldwide. We refer to Beck et al. (2019b) for a comprehensive description of the dataset.

#### *2.1.1. Quality Control*

The integration of erroneous gauge observations into MSWEP-V2.2 can occasionally result in implausible precipitation values. Therefore, we implemented a three-step quality control procedure of the 3-hourly data prior to the analysis. We first discarded negative values, which are physically impossible. The second step was to discard outliers, which we defined as values deviating from the mean by more than 30 standard deviations. We also discarded data surrounding the outliers for the same time step using a $11 \times 11$ grid-cell window, as erroneous gauge observations may have influenced surrounding cells in the production of the MSWEP dataset. The third step was to discard years with $> 30$ missing days or $< 5$ 'wet' 3-hourly periods, identified using a threshold of 0.2 mm $3h^{-1}$ following Wasko et al. (2015). Finally, we only included in the analysis data from grid cells with at least 30 years of data remaining, as a minimum record length of 30 years is customary and recommended to obtain reliable results (Arguez and Vose, 2011; Kendon et al., 2018; Westra et al., 2013).

#### *2.1.2. Durations and Identification of Independent Events*

The durations we selected for our analysis are 3, 6, 12 and 24 hours, and 2, 3, 5 and 10 days. In order to create statistically-independent precipitation events for multiple durations, we first separated 3-hourly events following the declustering method to limit the autocorrelation of the samples described in Marra et al. (2018, their Section 3.1). For longer durations, independent

events are the maximum intensities within each independent event and non-overlapping period using moving windows (Marra et al., 2020).

### *2.1.3. Hydrological Year*

A common challenge in global-scale assessments is the delineation of the hydrological year, given the regional variability in the climatological precipitation seasonality. We therefore developed an uniform way to define the hydrological year. To avoid splitting one rainy season over two different years, we computed the median of the monthly precipitation for each grid-cell, and defined the start of the hydrological year to be the first day of the driest month. Supplementary Material Figure S1a shows the starting month of the hydrological year as determined by this method. These data are also available in the GPEX dataset (Gründemann et al., 2021). As MSWEP-V2.2 spans the interval from 1 January 1979 to 31 October 2017, we discarded the data prior to the start of the first hydrological year, thus keeping 38 complete years. Only where the hydrological year starts in December there are just 37 complete years, which occurs in 5.8 % of the grid cells.

We also investigated whether there is a significant difference between the use of calendar and hydrological years for the estimated daily extremes for GEV and MEV. The POT method is based on the values over a high threshold, irrespective of when they occurred. Therefore, there is by definition no difference in calculating the extremes using hydrological or calendar years for the POT method. To determine the difference for GEV and MEV, we first calculated the daily return levels for normal calendar years, using the MSWEP data from 1979 to 2016. Second, we calculated the return levels for the same distributions and the same years, by removing the months before the start of the hydrological year from the year 1979 and adding them to the year 2016. We did this in order to use the exact same data, so the differences in the return level estimates are solely due to a different starting month.

## *2.2. Extreme Value Distributions*

Three extreme value distributions were fitted to the MSWEP data to calculate extreme precipitation return levels: the GEV, POT, and MEV distributions. Annual (hydrological year) maxima were used to estimate the three parameters of the GEV using the L-moments approach, because of its robust performance for small samples (Hosking, 1990). The GEV cumulative

distribution function (CDF) is given by:

$$G(z) = \begin{cases} \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\}, \xi \neq 0 \\ \exp\left\{-\exp\left[-\left(\frac{z-\mu}{\sigma}\right)\right]\right\}, \xi = 0 \end{cases} \quad (1)$$

with location parameter $\mu \in (-\infty, \infty)$, scale parameter $\sigma > 0$, and shape parameter $\xi \in (-\infty, \infty)$. The annual extremes estimated by GEV are translated into those of the parent distribution, following Koutsoyiannis (2004a, equation 3).

As a second EV model we use a Peaks Over Threshold approach, describing precipitation accumulations exceeding a high threshold using a GP distribution, while modelling the frequency of threshold exceedances using a Poisson point process (Coles, 2001; Davison and Smith, 1990). This framework also yields GEV as the resulting extreme value distribution, which is then used to determine the quantile corresponding to a given return period. The GP CDF is given by:

$$H(y) = \begin{cases} 1-\left(1+\frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}}, \xi \neq 0 \\ 1-\exp\left(-\frac{y}{\beta}\right), \xi = 0 \end{cases} \quad (2)$$

where $y > 0$ are precipitation excesses over the threshold, with $\beta > 0$ and $\xi \in (-\infty, \infty)$ the GP scale and shape parameters respectively. A relevant aspect in applying the POT model is a suitable choice of the threshold used to define precipitation exceedances. Our global-scale application requires studying the distribution of precipitation extremes across markedly different climatic regions, thus excluding the adoption of a constant threshold value. We studied the effect of the threshold choice using multiple threshold selection methods on a global sample of grid cells (see Supplementary Material Section 2 and and Figure S2). Our results showed that this choice had a limited effect on the estimated return levels (Figure S2a). We chose to perform our global analysis by selecting for each cell a threshold value such that it is exceeded on average 3 times each hydrological year. As a consequence of this choice, the sample size available for fitting the GP distribution remains constant across different precipitation durations. The method used to fit the GP distributions is the Probability Weighted Moments (PWM; e.g., see Hosking and Wallis, 1987).

The third model applied here is the MEV distribution (Hosseini et al., 2020; Hu et al., 2020; Marani and Ignaccolo, 2015; Miniussi et al., 2020a,b;

Zorzetto et al., 2016). In the MEV framework, all "ordinary" precipitation events, i.e. all events above a small threshold, are used to infer this EV distribution. The threshold we applied is 0.2 mm $3h^{-1}$, coinciding with the earlier defined 'wet event'. Weibull parameters were estimated for each hydrological year separately, based on all wet events using the PWM method (Greenwood et al., 1979) as done in Zorzetto et al. (2016). The MEV-Weibull CDF is given by:

$$\zeta_m(x) = \frac{1}{M} \sum_{j=1}^{M} \left\{ 1 - \exp\left[ - \left( \frac{\mathrm{x}}{\mathrm{C_j}} \right)^{\mathrm{w_j}} \right] \right\}^{n_j} \tag{3}$$

where $j$ is the hydrological year ($j = 1, 2, \ldots, M$), $C_j > 0$ is the Weibull scale parameter, $w_j > 0$ is the Weibull shape parameter, and $n_j$ is the number of wet events observed in hydrological year $j$ (Marani and Ignaccolo, 2015).

### *2.2.1. Observed Return Period*

The MSWEP dataset analyzed here has 38 complete years of data. Therefore, the empirical return period associated with the maximum value on record computed according to the Weibull empirical frequency estimate is $T_{\text{observed}} = 39$ years. However, only 91 % of all cells had 38 complete years of data, so the maximum observed return period is sometimes lower: for 7 % of the cells only 37 complete years were available, and for 2 % of the cells 36 years or less were available. However, for simplicity we still refer to the corresponding maximum return level as T39 in the results.

### *2.2.2. Tail Behavior*

Both the GEV and MEV distributions are flexible and can describe different tail behaviors. They are, therefore, appropriate models to study the characteristics of local precipitation extremes. The tail behavior of the two distributions differs, as illustrated in Figure S3 for different combinations of scale and shape parameters. The shape parameter $\xi$ of the GEV distribution, obtained either through the annual maxima or POT approach, encodes the nature of the tail of the distribution. Based on the value of $\xi$, the GEV can take one of three forms: a positive GEV shape parameter ($\xi > 0$, *"Fréchet"*) corresponds to a power-law tail, i.e., to a slowly-decaying probability of large events. This heavy-tail behavior contrasts with the case of an exponential tail ($\xi = 0$, *"Gumbel"*), and with the case of a distribution with an upper end

point, which corresponds to negative values of the shape parameter ($\xi < 0$, *"inverse Weibull"*).

The MEV distribution assumes that precipitation events are Weibull-distributed. The tail decay of this distribution is controlled by its shape parameter: for $w < 1$ its tail behavior is "sub-exponential", i.e., heavier than that of an exponential (recovered for $w = 1$), albeit with a characteristic scale (Laherrere and Sornette, 1998; Wilson and Toumi, 2005). For $w > 1$ the Weibull tail is super-exponential, with a fast decaying tail, while still retaining an infinite upper end point. Hence, the shape parameter of the Weibull distribution encodes the propensity of a site to be subjected to large extreme events (Wilson and Toumi, 2005; Zorzetto et al., 2016). However, the tail decay of the MEV distribution is not only dependent on that of ordinary values (through $w$) but is also affected by the yearly number of events (Marra et al., 2018) and by the inter-annual variations of $C_j$, $w_j$ $n_j$.

In an effort to compare the heaviness between the distributions, we have come up with a measure of heaviness that is based on the return levels themselves (Figure 1). The difference between the 1000-year return level and the 10-year return level can be described as follows:

$$\mathrm{T1000} = \mathrm{T10} + b + b + a \tag{4}$$

Where $b$ is the difference between the 100-year and 10-year return level, i.e.: $b = \mathrm{T100} - \mathrm{T10}$, and $a$ is the additional increase caused by the heaviness of the tail (Figure 1). A positive $a$ is indicative of heavy tails and a negative $a$ of thin tails. For pure exponential tails it holds that $a = 0$. The value for $a$ is highly dependent on the local precipitation systems, so we defined the heaviness amplification factor $h$ to be a normalization of $a$:

$$h = \frac{a}{b} = \frac{\mathrm{T1000} - 2 \times \mathrm{T100} + \mathrm{T10}}{\mathrm{T100} - \mathrm{T10}} \tag{5}$$

In words, the meaning of $h$ is the fractional additional increase between T1000 and T100 that is more than the increase that could be expected from a pure exponentially tailed distribution. A distribution has a heavy tail for $h > 0$ and a thin tail for $h < 0$.

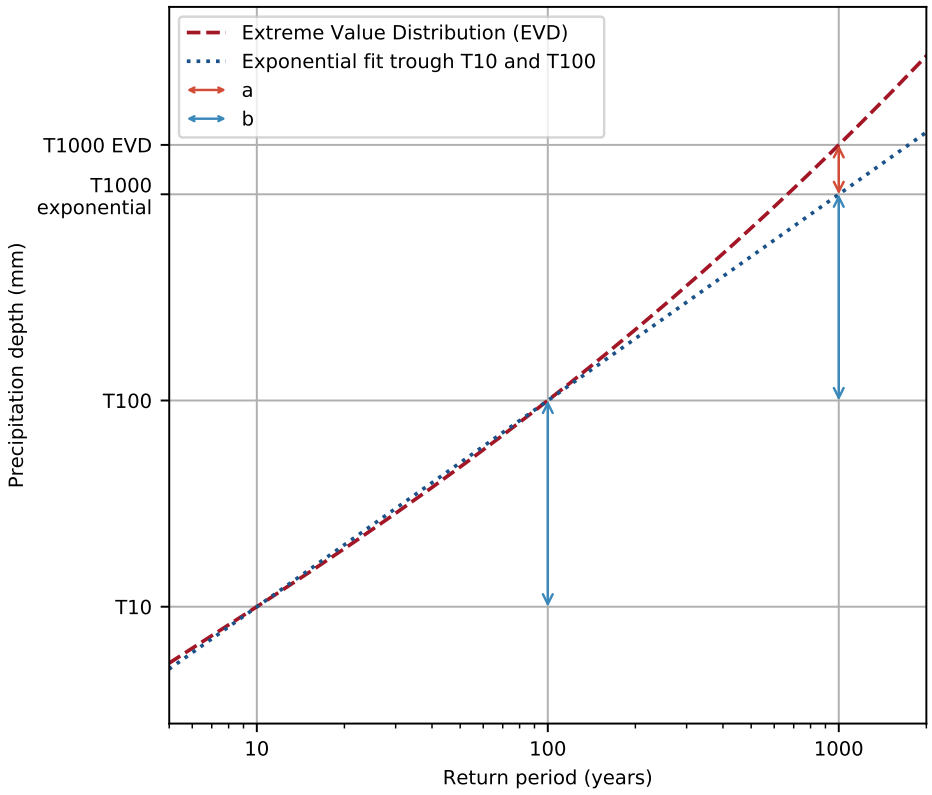


Figure 1: Illustration of our method to measure the tail heaviness for any distribution based on return levels only.

## 3. Results and Discussion

### *3.1. Hydrological Year*

Figure 2 shows the frequency distribution of 1000-year return levels estimated using calendar and hydrological years for GEV and MEV. The spatial distribution of these differences is presented in Supplementary Material Figure S1b for GEV and Figure S1c for MEV. We found that in the case of GEV quantiles, the fraction of sites characterized by differences within $\pm 0.5\,\%$ is larger than that observed for MEV. When the hydrological year starts in the winter months, the hydrological year is only shifted by a few months. In such instances, the annual maxima mostly stay the same between the calendar and hydrological years, though the included events could differ. For GEV this means that for many cells there is almost no difference in the T1000 estimates, whereas for MEV the difference is small.

On the other hand, when the offset with a calendar year is approximately 6 months, around June, there are many different events included in the hydrological years compared to the calendar years. This results in different annual maxima and large differences in the estimated extremes for GEV and MEV. The differences are most pronounced in the Southern hemisphere and in locations where the hydrological year starts around June, e.g., in the Mediterranean region, in the Middle-East, in Southern Africa, in Brazil, around Indonesia, and in the western US (Figure S1a). For MEV the overall sensitivity remains lower than that of GEV. In particular, the distribution of differences in Figure 2 exhibits thicker tails for GEV (e.g., as measured by the wider 5th to 95th percentile interval). This suggests that regional sensitivity to the definition of block maxima can be quite significant for the GEV approach.

### *3.2. Extreme Precipitation Estimates*

Figure 3 shows the 100-year precipitation return levels for a 24-hour duration. Extreme value estimates for other durations and return periods are featured in the Global Precipitation EXtremes (GPEX) dataset (Gründemann et al., 2021). The spatial patterns of the extremes estimated by GEV and MEV are similar to Zorzetto and Marani (2020, their Figure 9), while the spatial pattern of the underlying GEV parameters are consistent with Courty et al. (2019, their Figure 1). The global spatial pattern of return levels for the three EV methods is similar, although large regional differences can be observed. The GEV and POT results are similar in magnitude and show similar

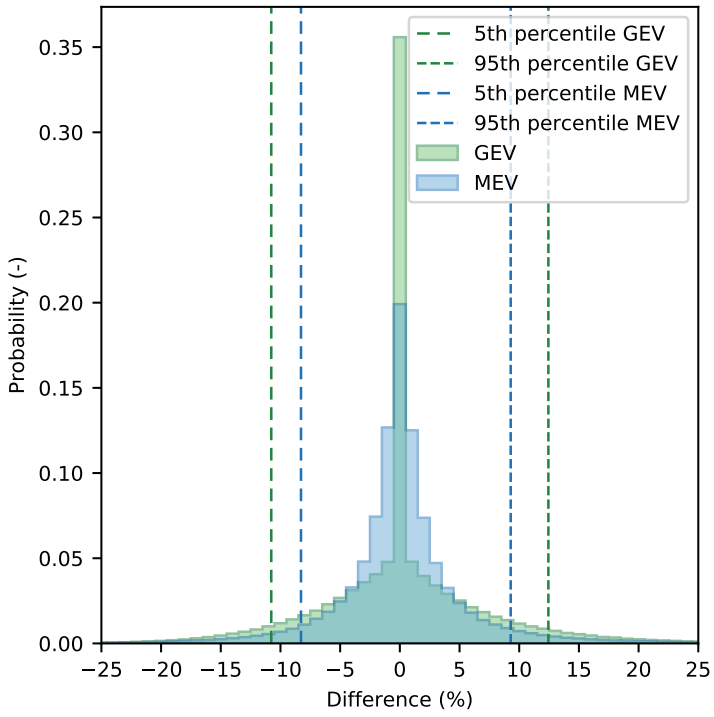


Figure 2: Weighted histogram showing the percentage difference in the values of T1000 quantiles calculated using calendar years and hydrological years. Included in the figure are all cells where the start of the hydrological year is different than the calendar year (i.e., the hydrological year does not start in January, see Supplementary Material Figure 1a). A negative difference indicates that the T1000 estimate is larger using hydrological years, whereas a positive difference indicates that the T1000 estimate is larger using calendar years.

differences when compared to MEV. The estimated precipitation extremes are generally lower for both GEV and POT compared to MEV quantiles. MEV estimates exhibit smooth spatial patterns, whereas the spatial patterns using GEV and POT are more irregular, consistent with the results of Zorzetto and Marani (2020) for the conterminous US. The reduced spatial coherence in patterns of extremes for GEV and POT is particularly evident in the Great Plains of North America, and in Northern Russia, Southeast Asia, and Central Africa. Furthermore, our analysis (Figure 3) reveals the presence of a large number of circular areas with heavier extremes, corresponding to the location of gauges used for correcting precipitation estimates in the

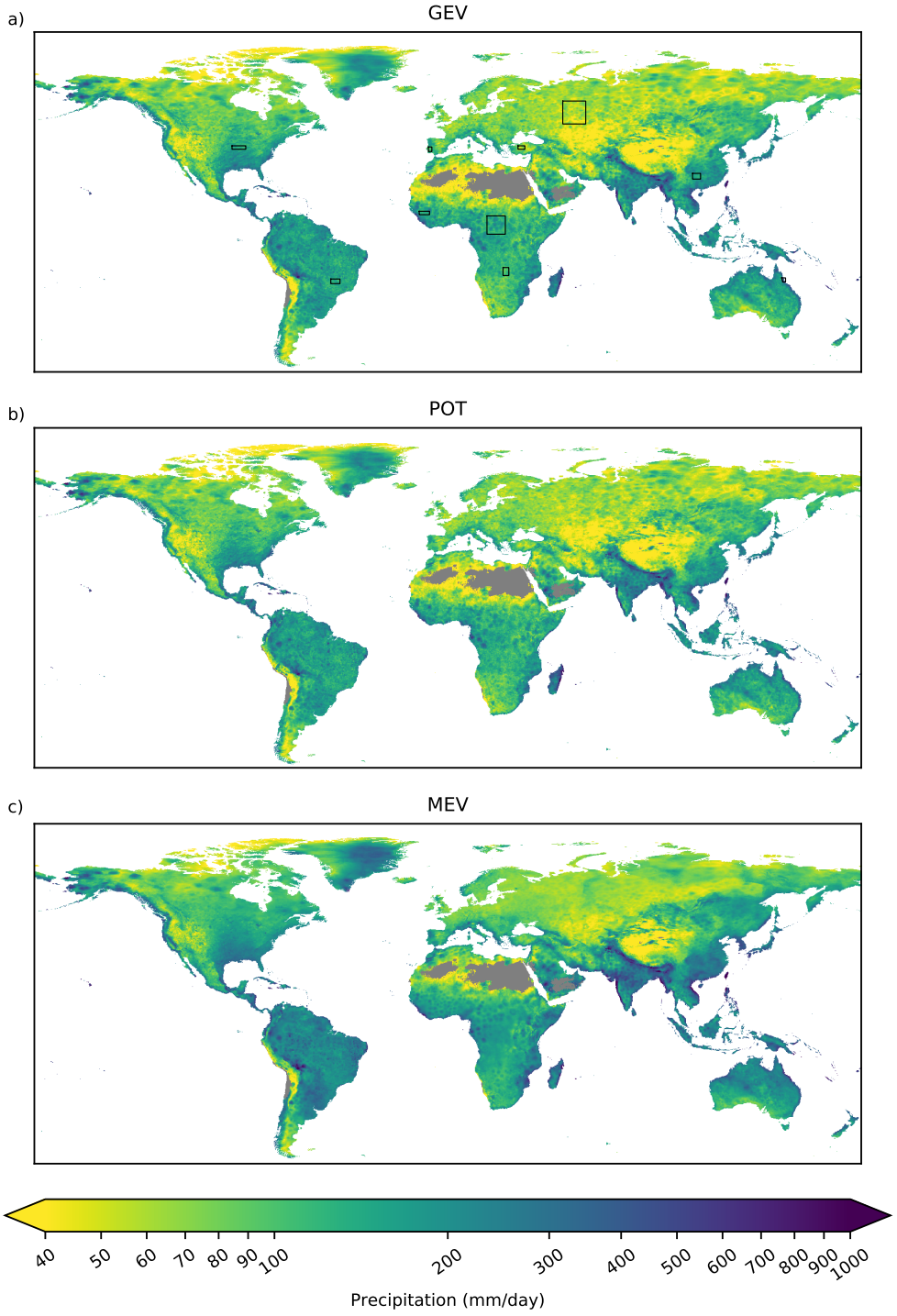


Figure 3: Precipitation return levels with a duration of 24-hours for a 100-year return period for different extreme value distributions: (a) the Generalized Extreme Value (GEV) distribution, (b) the Peak Over Threshold (POT) method, and (c) the Metastatistical Extreme Value (MEV) distribution. The black rectangles in panel a are the case studies corresponding to the areas in Figure 4.

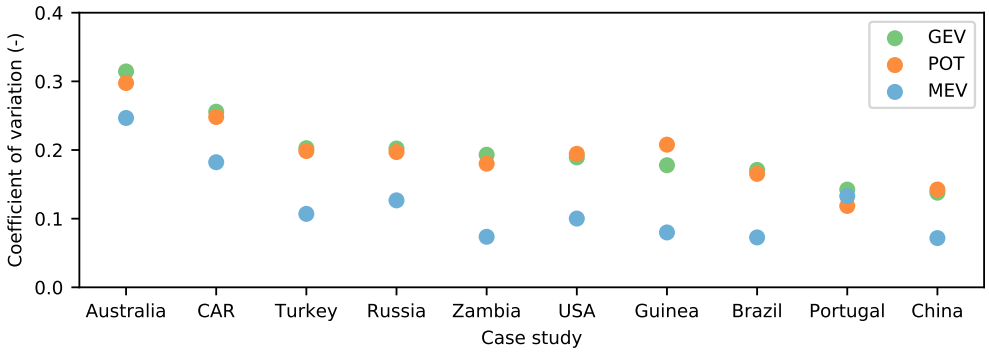


Figure 4: Coefficient of variation for the difference in estimated T100 quantiles for the three extreme value methods for 24-hour precipitation at selected case study areas. The coefficient of variation is the standard deviation of the precipitation divided by the mean precipitation. The locations of the case study areas are displayed in Fig 3a.

MSWEP algorithm (Beck et al., 2019b). The effect of these local corrections is much larger for traditional EV models (POT and GEV), while MEV appears less sensitive to these local corrections.

In order to study the ability of the three distributions to capture the spatial coherence of precipitation extremes, we selected several case study areas. They collectively cover a wide range of climates and domain sizes, the locations of which can be found in Figure 3a. Within a single case study area, we expect the precipitation estimates to be statistically homogeneous because of their precipitation generating mechanisms (Cavanaugh and Gershunov, 2015; Cavanaugh et al., 2015) or elevation (Ragulina and Reitan, 2017). Figure 4a shows the coefficient of variation (CV) of T100 extreme precipitation estimates for these case studies. The CV is the ratio of the standard deviation to the mean and is used to compare the relative variation between the study areas. The higher the CV, the higher the relative spread of the precipitation estimates within a spatial domain. This figure shows quite similar behavior for GEV and POT, though POT has a slightly lower spread. The CV for MEV is lower, which points to more spatially coherent T100 precipitation estimates based on single point time series (with 38 years of training data).

To further investigate the global differences in magnitude between the three methods, we examine the extremes for each distribution using a spatially weighted mean over the global land surface. This is displayed for

multiple return periods and durations as depth-duration-frequency curves (Figure 5). We first compare the maximum precipitation observed in the dataset to the precipitation predicted from each distribution. As there are 38 complete years of MSWEP data, the maximum empirically observed return level is 39 years (T39 observed, the black dotted line in Figure 5). While locally the empirical T39 estimate could be very different from the true return level, we expect the global average of this value to be representative of the true T39. For GEV and POT, we expected the estimated T39 to be close to the observed value since only the largest values are used to fit these distributions. For MEV, we did not necessarily expect a good agreement for T39, but its performance should be better for return levels greater than the length of the observation time series (Marra et al., 2018, 2019b; Schellander et al., 2019; Zorzetto et al., 2016). The results in Figure 5 show that for the lower duration events, the observed T39 is close to the T39 for all three distributions. For increasing durations, the deviation between empirically observed and EV modeled T39 quantiles increases, particularly for MEV. Both GEV and POT show an underestimation and MEV an overestimation. This figure also shows again that the differences between GEV and POT are small. The global average estimated extremes for GEV and POT are notably lower than for MEV, as was already visible from Figure 3. This difference is more pronounced for larger return periods and longer durations.

One reason the quantiles estimated using MEV are higher than using GEV and POT is related to the increase in estimation uncertainty of Weibull parameters when the number of events per hydrological year is low. This is especially relevant in arid regions and for long durations. For instance, for 5 and 10-day durations the average annual number of events is 36 and 21 events respectively. It is therefore possible that this leads to an overestimation by MEV. To overcome this, windows of two or more years could result in a better parameter estimation (Miniussi and Marani, 2020). A second factor which may be relevant relevant for MEV quantile estimates is the use of a fixed threshold for defining a precipitation event.

### *3.3. Tail Behavior*

To better understand the differences between extremes estimated using the three extreme value methods, we analyze their tail behavior using the heaviness amplification factor $h$ (Eq. 5). Figure 6 presents $h$ for a 24-hour duration worldwide for each of the three distributions. We refer to Figures S5-S11 in Section 4 in the supplementary material for maps of $h$ for the other

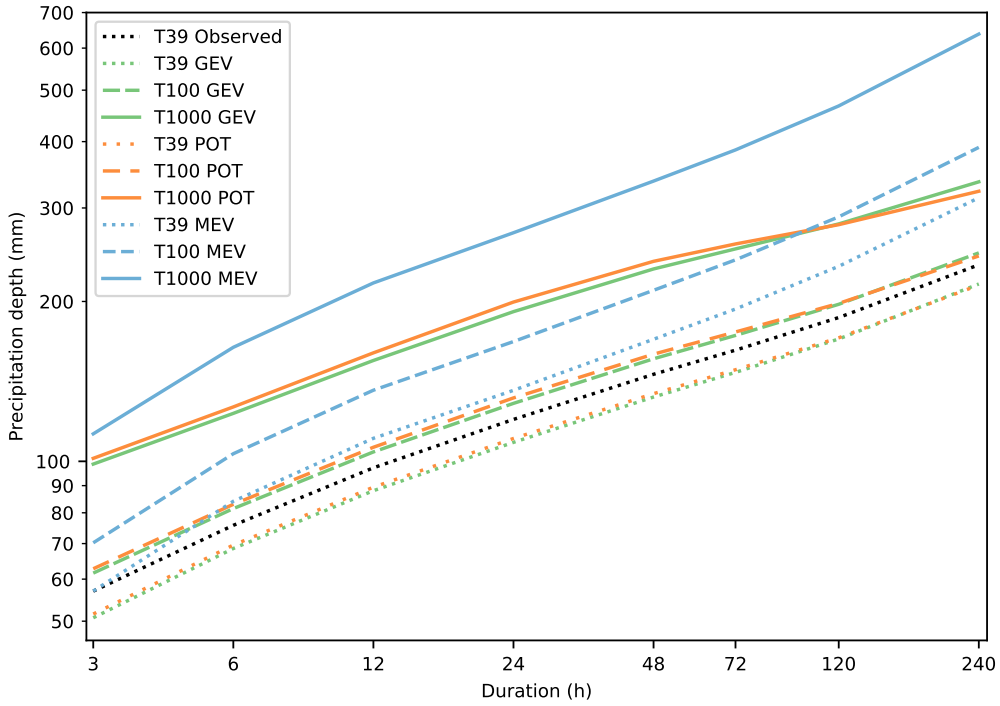


Figure 5: Area-weighted average depth-duration-frequency curves for the global land surface. T39 Observed is the mean spatially weighted maximum precipitation observed in the MSWEP-V2.2 dataset.

durations. Both GEV (Figure 6a) and POT (Figure 6b) exhibit a large spatial variability in addition to a low spatial coherence. This makes it difficult to discern clear spatial patterns with the exception of a few notable regions. For instance, in the Amazon, $h$ is mostly negative, suggesting a tail with an upper limit, while in Eastern and Southern Australia $h$ it is strongly positive, denoting strong heavy tail behavior. This map roughly corresponds to the spatial patterns of the daily GEV shape parameter shown by Papalexiou and Koutsoyiannis (2013, their Figure 13) and Ragulina and Reitan (2017, their Figure 4). We also find that for the GEV and POT methods, grid cells associated with heavy tails can be adjacent to cells with thin tails. Furthermore, GEV and POT do not always show the same type of tail, heavy or thin, in the same grid cells. In 72 % of the cases the sign of the underlying shape parameter agrees, while in 28 % of the cases the signs are different for daily precipitation. This highlights the large uncertainty

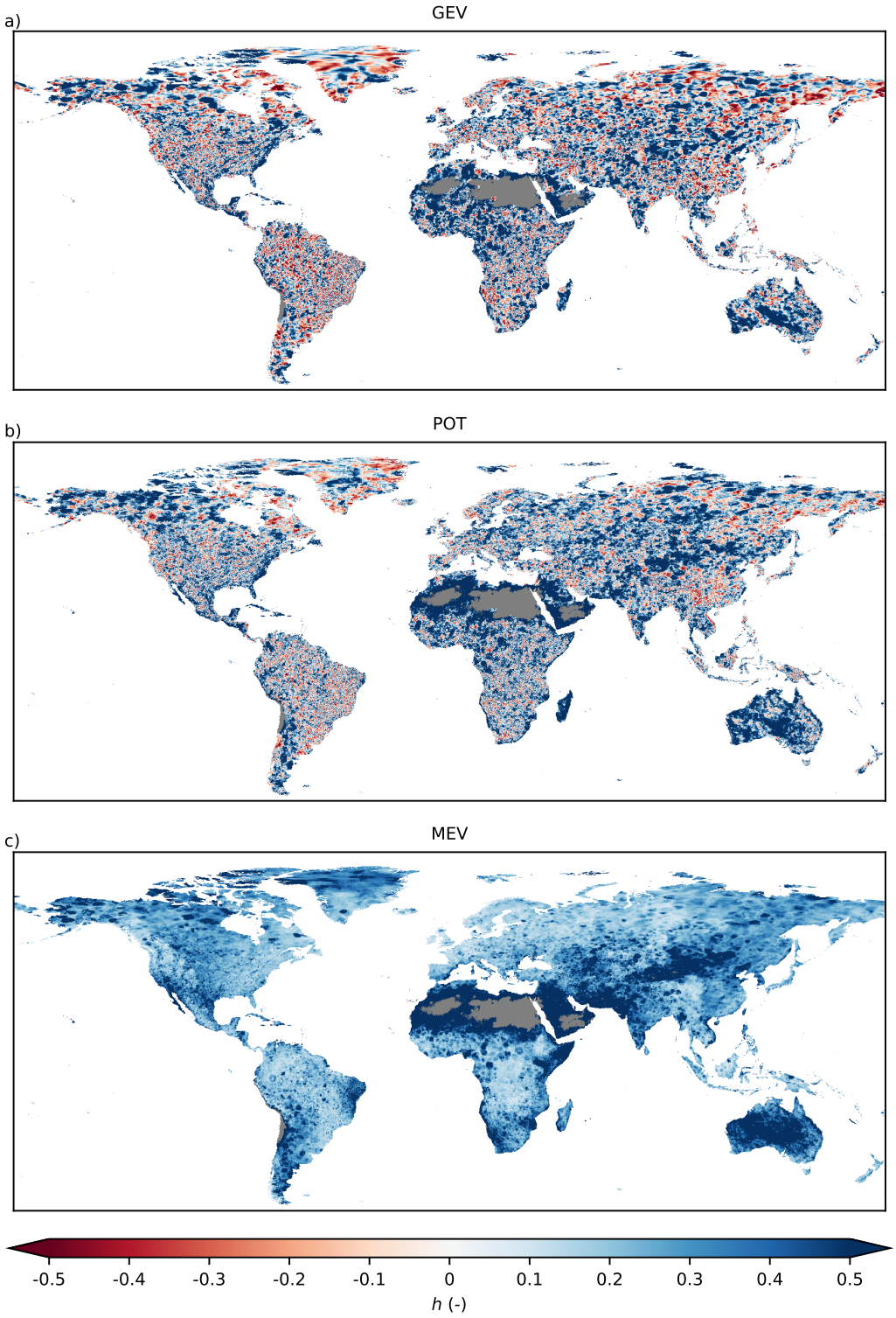




Figure 6: The heaviness amplification factor $h$ (Eq. 5) for daily precipitation calculated for different extreme value methods: (a) GEV, (b) POT, (c) MEV. Red indicates a thin tail, white an exponential tail, and blue a heavy tail. See section 2.2.2 for more information on the heaviness metric, and Figures S5-S11 for maps of $h$ for the other durations.

associated with estimating reliable tail parameters from short time series and the sensitivity of the GEV and POT methods to sampling effects.

The heaviness of the MEV distribution (Figure 6c) shows a more coherent spatial pattern. At virtually all grid cells the heaviness amplification factor $h$ (Eq. 5) indicates heavy tail behavior and there is a high consistency within geographic regions and for all durations (Figures S5-S11). Based on previous studies (Cavanaugh et al., 2015; Papalexiou and Koutsoyiannis, 2013; Papalexiou et al., 2013; Ragulina and Reitan, 2017), this predominantly heavy-tail behavior of daily precipitation was expected and is well captured by MEV. There are also topographical patterns visible in the heaviness amplification factor (Figure 6c), though they are not as clearly distinguishable as for the shape parameter itself (Figure S4). The heaviness tends to be higher in arid areas, and lower in mountainous areas. Examples of arid areas with high heaviness include the Sahara, the Namib and Kalahari in Africa, the Gobi, Thar and Taklamakan in Asia, the Atacama Desert in South America, large areas of Southwestern Australia, and the Arabian desert and other areas in the Middle East. This same pattern is to a lesser extent also visible for the heaviness of GEV (Figure 6a) and POT (Figure 6b).

At high elevations a small $h$ is usually found for MEV (Figure 6c). Examples include the Rocky Mountains and the Sierra Madres in North America, the northern Andes and large areas of the Brazilian Highlands in South America, the Ethiopian Highlands, the Scandinavian Mountains, and the Tibetan Plateau. These spatial patterns are in contrast with what Papalexiou et al. (2018, their Figure 6) found for hourly Weibull tails in the USA, where the heaviest tails are in the mountainous areas, and the thin tails are in the south-east. However, our results correspond well to Ragulina and Reitan (2017, their Figure 4), who showed that heaviness decreases with elevation.

A comparison of the heaviness for different distributions and durations is presented as a boxplot in Figure 7. For spatial maps of the heaviness for the different durations we refer to Figures S5-S11. For GEV and POT, predominantly heavy tails are observed for short durations and thinner tails for long durations. Furthermore, GEV and POT both show a decreasing variability in the heaviness for longer durations, indicated by both shorter whiskers and boxes. The decrease of the heaviness of the tails for increasing durations is in line with the findings of Cavanaugh and Gershunov (2015), who found that longer duration extremes exhibit thinner tails. For GEV and POT the longer durations largely indicate tails with a finite upper end point. This occurs for instance in half of the cases for a duration of 10

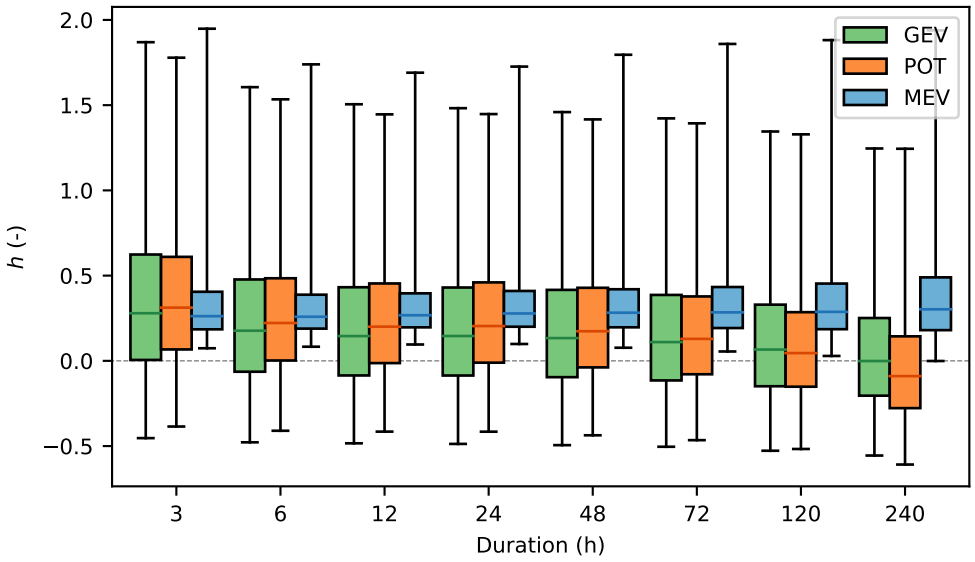


Figure 7: Boxplots showing the distribution of the heaviness amplification factor $h$ (-) for different durations and extreme value methods: (a) GEV and POT, and (b) MEV. The whiskers denote the 1st and 99th percentiles. The top and bottom of the boxes represent the 75th and 25th percentiles, respectively. The dashed gray horizontal lines indicate exponential tails. See section 2.2.2 for more information on the heaviness metric.

days for GEV, and more than half for POT. One implication of this finding is that, when computing return levels for a single location (see Figures S3 and S12), it is possible for the very large return periods that the shorter duration quantiles are more intense than the longer duration quantiles. This is physically impossible (see Figure S12a,b,e and f), and we should thus be extremely careful when interpreting such results.

MEV, on the other hand, shows different heaviness patterns than GEV and POT (Figure 7 and Figures S5-S11). MEV shows almost entirely a heavy-tail behavior, which remains consistent across the range of durations examined. Furthermore, also the variability for MEV is constant across durations, though with a slight increase for longer durations. The MEV distribution thus produces a spatially and temporally coherent heavy tail behavior based on a 38 years calibration sample and a single grid-cell analysis. This is a promising result, as MEV, in contrast to the traditional methods analyzed, provides essential information on the spatial coherence of precipitation extremes without any prior hypothesis on its spatial structure, for example through a spatial clustering scheme (Demirdjian et al., 2018). In fact, the spatial structure of the tail heaviness obtained through the MEV analysis could be used as a measure of statistical homogeneity for regionalization studies.

## 4. Conclusions

The aim of this research was to quantitatively characterize the spatiotemporal variation of global precipitation extremes and their associated extreme value distribution tails. We have fitted three different extreme value methods (GEV, POT, and MEV) to a global precipitation dataset, MSWEP V2.2, to estimate extreme precipitation return levels for several durations. In order to compare the tails of the three distributions, we introduced the heaviness amplification factor $h$ (Eq. 5). Instead of using calendar years to delineate between different years, we used hydrological years. We demonstrated that there is a substantial difference in the extremes depending on the definition of yearly blocks used in the extreme value analysis (Figure 2). These differences were most notable in the Southern hemisphere, and in locations where the driest month occurs around June (Figure S1). Although there is no systematic bias, we still recommend to apply the extreme value analyses for estimating extreme precipitation based on hydrological years in future

studies. Our analysis indicates that this can be particularly relevant in the Southern hemisphere and in regions characterized by marked seasonal cycles.

It is well known that the traditional GEV and POT methods require very long data-series for accurate estimation of the tail behavior, and our study confirms that there is a low spatial coherence for the tail properties of both distributions (Figure 6a and b) using just 38 years of training data. The tail properties of the MEV distribution are spatially more coherent (Figure 6c) and hence the estimated return levels are more spatially coherent as well (Figure 3c). This spatially coherent behavior, consistent with previous results obtained over the conterminous US (Zorzetto and Marani, 2020), shows that the MEV distribution is able to capture spatially consistent tail behavior from short time series and by a single grid-cell analysis, without any prior information on the spatial precipitation structures. The analysis of the MEV tail behavior reveals distinct spatial patterns, as the heaviness appears to be controlled by climate zones and orography. Heavier tails are observed in arid areas, and thinner tails in mountainous regions. More in-depth analyses are necessary to draw definite conclusions on what exactly controls the heaviness of extreme value distribution tails. The performance of MEV is promising for regions without long local precipitation records. Furthermore, our study shows that the tail behavior captured by MEV is coherent and heavy both spatially and temporally (Figures 6, 7 and S5-S11). For GEV and POT, on the other hand, the tail behavior decreases with increased event duration, resulting in a thin tail with a finite endpoint for about half of the cells for a duration of 10 days.

We also conclude that both GEV and POT generally underestimate the observed extremes, whereas MEV overestimates them (Figure 5). This occurs particularly for long-duration extremes and large return periods. We do consider it likely, however, that the results could be improved, for instance by changing the event threshold or by fitting the Weibull distribution over two or more years for dry areas (Miniussi and Marani, 2020), so as to reduce inter-annual variability of the parameters due to samples of limited length. Our results suggest that this issue is particularly relevant at the longest durations examined. For GEV and POT the results could also be improved by adopting spatial models (Davison et al., 2012; Huser and Wadsworth, 2020).

The data generated for this study are openly available as the GPEX dataset (Gründemann et al., 2021). These data include extreme precipitation return levels and extreme value distribution parameters for durations between

3 hours and 10 days at a global gridded 0.1° resolution. They could be used by engineers as a reference of precipitation extremes for data-scarce regions in particular. For scientific purposes, all underlying parameters are also available and can be used to answer several outstanding questions, such as: what are the controls on the tail behavior of extremes, and what is driving the different changes in tail heaviness with duration for GEV, POT, and MEV?.

## Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The GPEX dataset is available at the 4TU repository Gründemann et al. (2021). The data included are the extremes estimated using the different distributions, the observed extremes, and the parameters to estimate the extremes. These data are available for all durations included in this study. The resolution of the dataset is 0.1°, the resolution of the MSWEP-V2.2 dataset. For more information we refer to the Dataset Usage Notes in Section 5 of the supplementary material.

## References

Alijanian, M., Rakhshandehroo, G.R., Mishra, A.K., Dehghani, M., 2017. Evaluation of satellite rainfall climatology using CMORPH, PERSIANN-

552 CDR, PERSIANN, TRMM, MSWEP over Iran. International Journal of
553 Climatology 37, 4896–4914. doi:10.1002/joc.5131.

554 Allan, R.P., Soden, B.J., 2008. Atmospheric warming and the amplification
555 of precipitation extremes. Science 321, 1481–1484. doi:10.1126/science.
556 1160787.

557 Arguez, A., Vose, R.S., 2011. The definition of the standard WMO cli-
558 mate normal: The key to deriving alternative climate normals. Bul-
559 letin of the American Meteorological Society 92, 699–704. doi:10.1175/
560 2010BAMS2955.1.

561 Bai, P., Liu, X., 2018. Evaluation of five satellite-based precipitation products
562 in two gauge-scarce basins on the Tibetan Plateau. Remote Sensing 10.
563 doi:10.3390/RS10081316.

564 Ball, J., Babister, M., Nathan, R., Weeks, W., Weinmann, E., Retallick,
565 M., Testoni, I., 2019. Australian Rainfall and Runoff: A guide to flood
566 estimation. Commonwealth of Australia (Geoscience Australia).

567 Beck, H.E., Pan, M., Roy, T., Weedon, G.P., Pappenberger, F., van
568 Dijk, A.I.J.M., Huffman, G.J., Adler, R.F., Wood, E.F., 2019a. Daily
569 evaluation of 26 precipitation datasets using Stage-IV gauge-radar data
570 for the CONUS. Hydrology and Earth System Sciences 23, 207–224.
571 doi:10.5194/hess-23-207-2019.

572 Beck, H.E., Vergopolan, N., Pan, M., Levizzani, V., van Dijk, A.I.M., Wee-
573 don, G.P., Brocca, L., Pappenberger, F., Huffman, G.J., Wood, E.F., 2017.
574 Global-scale evaluation of 22 precipitation datasets using gauge observa-
575 tions and hydrological modeling. Hydrology and Earth System Sciences
576 21, 6201–6217. doi:10.5194/hess-21-6201-2017.

577 Beck, H.E., Wood, E.F., Pan, M., Fisher, C.K., Miralles, D.G., van Dijk,
578 A.I.J.M., McVicar, T.R., Adler, R.F., 2019b. MSWEP V2 Global 3-
579 Hourly 0.1° Precipitation: Methodology and Quantitative Assessment.
580 Bulletin of the American Meteorological Society 100, 473–500. doi:10.
581 1175/BAMS-D-17-0138.1.

582 Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., Schamm, K.,
583 Schneider, U., Ziese, M., 2013. A description of the global land-surface

precipitation data products of the global precipitation climatology centre with sample applications including centennial (trend) analysis from 1901-present. Earth System Science Data 5, 71. doi:10.5194/essd-5-71-2013.

Beersma, J., Versteeg, R., Hakvoort, H., 2018. Neerslagstatistieken voor korte duren actualisatie 2018. Technical Report. STOWA. Amersfoort.

Casson, D.R., Werner, M., Weerts, A., Solomatine, D., 2018. Global re-analysis datasets to improve hydrological assessment and snow water equivalent estimation in a sub-arctic watershed. Hydrology and Earth System Sciences 22, 4685–4697. doi:10.5194/hess-22-4685-2018.

Cavanaugh, N.R., Gershunov, A., 2015. Probabilistic tail dependence of intense precipitation on spatiotemporal scale in observations, reanalyses, and GCMs. Climate Dynamics 45, 2965–2975. doi:10.1007/s00382-015-2517-1.

Cavanaugh, N.R., Gershunov, A., Panorska, A.K., Kozubowski, T.J., 2015. The probability distribution of intense daily precipitation. Geophysical Research Letters 42, 1560–1567. doi:10.1002/2015GL063238.

Coles, S., 2001. An introduction to statistical modeling of extreme values. Springer Series in Statistics; Springer: London, UK.

Contractor, S., Donat, M., Alexandre, L.V., Ziese, M., Meyer-Christoffer, A., Schneider, U., Rustemeier, E., Becker, A., Durre, I., Vose, R.S., 2020. Rainfall estimates on a gridded network (regen)–a global land-based gridded dataset of daily precipitation from 1950 to 2016. Hydrology and Earth System Sciences 24, 919–943. doi:10.5194/hess-24-919-2020.

Courty, L.G., Wilby, R.L., Hillier, J.K., Slater, L.J., 2019. Intensity-duration-frequency curves at the global scale. Environmental Research Letters 14, 084045. doi:10.1088/1748-9326/ab370a.

CRED, 2019. Natural disasters 2018. Technical Report. Institute Health and Society UClouvain. Brussels, Belgium. URL: https://www.cred.be/sites/default/files/CREDNaturalDisaster2018.pdf.

Davison, A.C., Padoan, S.A., Ribatet, M., et al., 2012. Statistical modeling of spatial extremes. Statistical science 27, 161–186.

615 Davison, A.C., Smith, R.L., 1990. Models for Exceedances over High Thresh-
616 olds. Journal of the Royal Statistical Society. Series B (Methodological)
617 52, 393–442. URL: https://www.jstor.org/stable/2345667.

618 De Paola, F., Giugni, M., Pugliese, M., Annis, A., Nardi, F., 2018.
619 GEV parameter estimation and stationary vs. non-stationary analysis
620 of extreme rainfall in African test cities. Hydrology 5. doi:10.3390/
621 hydrology5020028.

622 Decker, M., Brunke, M.A., Wang, Z., Sakaguchi, K., Zeng, X., Bosilovich,
623 M.G., 2012. Evaluation of the Reanalysis Products from GSFC, NCEP,
624 and ECMWF Using Flux Tower Observations. Journal of Climate 25,
625 1916–1944. doi:10.1175/JCLI-D-11-00004.1.

626 Demirdjian, L., Zhou, Y., Huffman, G.J., 2018. Statistical modeling of ex-
627 treme precipitation with trmm data. Journal of applied meteorology and
628 climatology 57, 15–30. doi:10.1175/JAMC-D-17-0023.1.

629 Donat, M.G., Alexander, L.V., Yang, H., Durre, I., Vose, R., Dunn, R.J.,
630 Willett, K.M., Aguilar, E., Brunet, M., Caesar, J., Hewitson, B., Jack,
631 C., Klein Tank, A.M., Kruger, A.C., Marengo, J., Peterson, T.C., Renom,
632 M., Oria Rojas, C., Rusticucci, M., Salinger, J., Elrayah, A.S., Sekele, S.S.,
633 Srivastava, A.K., Trewin, B., Villarroel, C., Vincent, L.A., Zhai, P., Zhang,
634 X., Kitching, S., 2013. Updated analyses of temperature and precipitation
635 extreme indices since the beginning of the twentieth century: The HadEX2
636 dataset. Journal of Geophysical Research: Atmospheres 118, 2098–2118.
637 doi:10.1002/jgrd.50150.

638 Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L.,
639 Randles, C.A., Darmenov, A., Bosilovich, M.G., Reichle, R., Wargan, K.,
640 Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A.,
641 Da Silva, A.M., Wei, G., Kim, G.K., Koster, R., Lucchesi, R., Merkova,
642 D., Nielsen, J.E., Partyka, G., Pawson, S., Putman, W., Rienecker, M.,
643 Schubert, S.D., Sienkiewicz, M., Zhao, B., 2017. The modern-era retro-
644 spective analysis for research and applications, version 2 (merra-2). Journal
645 of Climate 30, 5419–5454. doi:10.1175/JCLI-D-16-0758.1.

646 van de Giesen, N., Hut, R., Selker, J., 2014. The Trans-African Observatory
647 (TAHMO). WIREs Water 1, 341–348. doi:10.1002/wat2.1034.

Greenwood, J.A., Landwehr, J., Matalas, N., Wallis, J., 1979. Probability weighted moments: definition and relation to parameters of several distributions expressable in inverse form. Water Resources Research 15, 1049–1054. doi:10.1029/WR015i005p01049.

Gründemann, G.J., Werner, M., Veldkamp, T.I.E., 2018. The potential of global reanalysis datasets in identifying flood events in southern africa. Hydrology and Earth System Sciences 22, 4667–4683. doi:10.5194/hess-22-4667-2018.

Gründemann, G.J., Zorzetto, E., Beck, H.E., Schleiss, M., van de Giesen, N., Marani, M., van der Ent, R.J., 2021. Global Precipitation EXtremes dataset. doi:10.4121/uuid:12b5c941-cd54-45db-8d7b-fefaacecaa69.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horanyi, A., Munoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G.D., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Holm, E., Janiskova, M., Keeley, S., Laloyaux, P., Lopez, P., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thepaut, J.N., 2020. The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society , 1–51doi:10.1002/qj.3803.

Hong, Y., Hsu, K.L., Sorooshian, S., Gao, X., 2004. Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system. Journal of Applied Meteorology 43, 1834–1853. doi:10.1175/JAM2173.1.

Hosking, J.R.M., 1990. L-Moments: Analysis and estimation of distributions using linear combinations of order statistics. Journal of the Royal Statistical Society. Series B (Methodological) 52, 105–124.

Hosking, J.R.M., Wallis, J.R., 1987. Parameter and Quantile Estimation for the Generalized Pareto Distribution Parameter and Quantile Estimation Generalized Pareto Distribution. Technometrics 23, 339–349. doi:https://doi.org/10.1080/00401706.1987.10488243.

Hosseini, S.R., Scaioni, M., Marani, M., 2020. Extreme Atlantic Hurricane Probability of Occurrence Through the Metastatistical Extreme Value Distribution. Geophysical Research Letters 47, 1–9. doi:10.1029/2019GL086138.

Hu, L., Nikolopoulos, E.I., Marra, F., Morin, E., Marani, M., Anagnostou, E.N., 2020. Evaluation of MEVD-based precipitation frequency analyses from quasi- global precipitation datasets against dense rain gauge networks. Journal of Hydrology 590, 125564. doi:10.1016/j.jhydrol.2020.125564.

Huffman, G.J., Bolvin, D.T., Braithwaite, D., Hsu, K., Joyce, R., Kidd, C., Nelkin, E.J., Xie, P., 2015. NASA Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG): Algorithm Theoretical Basis Document (ATBD) Version 4.5. Technical Report. NASA/GSFC, Greenbelt, MD 20771, USA.

Huser, R., Wadsworth, J.L., 2020. Advances in statistical modeling of spatial extremes. Wiley Interdisciplinary Reviews: Computational Statistics , e1537.

Joyce, R.J., Janowiak, J.E., Arkin, P.A., Xie, P., 2004. CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. Journal of Hydrometeorology 5, 487–503.

Kendon, E.J., Blenkinsop, S., Fowler, H.J., 2018. When will we detect changes in short-duration precipitation extremes? Journal of Climate 31, 2945–2964. doi:10.1175/JCLI-D-17-0435.1.

Kidd, C., Becker, A., Huffman, G.J., Muller, C.L., Joe, P., Skofronick-Jackson, G., Kirschbaum, D.B., 2017. So, how much of the Earth's surface is covered by rain gauges? Bulletin of the American Meteorological Society 98, 69–78. doi:10.1175/BAMS-D-14-00283.1.

Kobayashi, S., Ota, Y., Harada, Y., Ebita, A., Moriya, M., Onoda, H., Onogi, K., Kamahori, H., Kobayashi, C., Endo, H., et al., 2015. The jra-55 reanalysis: General specifications and basic characteristics. Journal of the Meteorological Society of Japan 93, 5–48. doi:10.2151/jmsj.2015-001.

712 Koutsoyiannis, D., 2004a. Statistics of extremes and estimation of extreme
713 rainfall: I. Theoretical investigation. Hydrological Sciences Journal 49,
714 575–590. doi:10.1623/hysj.49.4.575.54430.

715 Koutsoyiannis, D., 2004b. Statistics of extremes and estimation of extreme
716 rainfall: II. Empirical investigation of long rainfall records. Hydrological
717 Sciences Journal 49, 591–610. doi:10.1623/hysj.49.4.591.54424.

718 Laherrere, J., Sornette, D., 1998. Stretched exponential distributions in
719 nature and economy:"fat tails" with characteristic scales. The European
720 Physical Journal B-Condensed Matter and Complex Systems 2, 525–539.

721 Liu, Z., Liu, Y., Wang, S., Yang, X., Wang, L., Baig, M.H.A., Chi, W.,
722 Wang, Z., 2018. Evaluation of Spatial and Temporal Performances of
723 ERA-Interim Precipitation and Temperature in Mainland China. Journal
724 of Climate 31, 4347–4365. doi:10.1175/JCLI-D-17-0212.1.

725 Mailhot, A., Duchesne, S., 2009. Design criteria of urban drainage infras-
726 tructures under climate change. Journal of Water Resources Planning and
727 Management 136, 201–208. doi:10.1061/(asce)wr.1943-5452.0000023.

728 Marani, M., Ignaccolo, M., 2015. A metastatistical approach to rainfall
729 extremes. Advances in Water Resources 79, 121–126. doi:10.1016/j.
730 advwatres.2015.03.001.

731 Marani, M., Zanetti, S., 2015. Long-term oscillations in rainfall extremes
732 in a 268 year daily time series. Water Resources Research 51, 639–647.
733 doi:10.1002/2014WR015885.

734 Marra, F., Borga, M., Morin, E., 2020. A unified framework for extreme
735 subdaily precipitation frequency analyses based on ordinary events. Geo-
736 physical Research Letters 47, e2020GL090209.

737 Marra, F., Nikolopoulos, E.I., Anagnostou, E.N., Bárdossy, A., Morin, E.,
738 2019a. Precipitation frequency analysis from remotely sensed datasets: A
739 focused review. Journal of Hydrology 574, 699–705.

740 Marra, F., Nikolopoulos, E.I., Anagnostou, E.N., Morin, E., 2018. Metas-
741 tatistical Extreme Value analysis of hourly rainfall from short records:
742 Estimation of high quantiles and impact of measurement errors. Advances
743 in Water Resources 117, 27–39. doi:10.1016/j.advwatres.2018.05.001.

744 Marra, F., Zoccatelli, D., Armon, M., Morin, E., 2019b. A simplified
745 MEV formulation to model extremes emerging from multiple nonstation-
746 ary underlying processes. Advances in Water Resources 127, 280–290.
747 doi:10.1016/j.advwatres.2019.04.002.

748 McGraw, D., Nikolopoulos, E.I., Marra, F., Anagnostou, E.N., 2019. Pre-
749 cipitation frequency analyses based on radar estimates: An evaluation
750 over the contiguous United States. Journal of Hydrology 573, 299–310.
751 doi:10.1016/j.jhydrol.2019.03.032.

752 Ménégoz, M., Gallée, H., Jacobi, H.W., 2013. Precipitation and snow
753 cover in the himalaya: from reanalysis to regional climate simulations.
754 Hydrology and Earth System Sciences 17, 3921–3936. doi:10.5194/
755 hess-17-3921-2013.

756 Miniussi, A., Marani, M., 2020. Estimation of daily rainfall extremes through
757 the metastatistical extreme value distribution: Uncertainty minimiza-
758 tion and implications for trend detection. Water Resources Research 56,
759 e2019WR026535. doi:10.1029/2019WR026535.

760 Miniussi, A., Marani, M., Villarini, G., 2020a. Metastatistical Extreme Value
761 Distribution applied to floods across the continental United States. Ad-
762 vances in Water Resources 136, 103498. doi:10.1016/j.advwatres.2019.
763 103498.

764 Miniussi, A., Villarini, G., Marani, M., 2020b. Analyses Through the Metas-
765 tatistical Extreme Value Distribution Identify Contributions of Tropical
766 Cyclones to Rainfall Extremes in the Eastern United States Geophysi-
767 cal Research Letters. Geophysical Research Letters 47, e2020GL087238.
768 doi:10.1029/2020GL087238.

769 Mishra, A.K., Coulibaly, P., 2009. Developments in hydrometric network
770 design: A review. Reviews of Geophysics 47. doi:10.1029/2007RG000243.

771 Nissen, K.M., Ulbrich, U., 2017. Increasing frequencies and changing charac-
772 teristics of heavy precipitation events threatening infrastructure in Europe
773 under climate change. Natural Hazards and Earth System Sciences 17,
774 1177–1190. doi:10.5194/nhess-17-1177-2017.

Overeem, A., Buishand, A., Holleman, I., 2008. Rainfall depth-duration-frequency curves and their uncertainties. Journal of Hydrology 348, 124–134. doi:10.1016/j.jhydrol.2007.09.044.

Papalexiou, S.M., Aghakouchak, A., Foufoula-Georgiou, E., 2018. A diagnostic framework for understanding climatology of tails of hourly precipitation extremes in the United States. Water Resources Research 54, 6725–6738. doi:10.1029/2018WR022732.

Papalexiou, S.M., Koutsoyiannis, D., 2013. Battle of extreme value distributions: A global survey on extreme daily rainfall. Water Resources Research 49, 187–201. doi:10.1029/2012WR012557.

Papalexiou, S.M., Koutsoyiannis, D., Makropoulos, C., 2013. How extreme is extreme? An assessment of daily rainfall distribution tails. Hydrology and Earth System Sciences 17, 851–862. doi:10.5194/hess-17-851-2013.

Perica, S., Pavlovic, S., St. Laurent, M., Trypaluk, C., Unruh, D., Martin, D., Wilhite, O., 2015. NOAA Atlas 14 Volume 10, Precipitation-Frequency Atlas of the United States, Northeastern States. Technical Report. NOAA, National Weather Service.

Perica, S., Pavlovic, S., St. Laurent, M., Trypaluk, C., Unruh, D., Wilhite, O., 2018. NOAA Atlas 14: Precipitation-frequency atlas of the United States, Texas. Technical Report. NOAA, National Weather Service.

Ragulina, G., Reitan, T., 2017. Generalized extreme value shape parameter and its nature for extreme precipitation using long time series and the Bayesian approach precipitation. Hydrological Sciences Journal 62, 863–879. doi:10.1080/02626667.2016.1260134.

Rasmusson, E.M., Arkin, P.A., 1993. A global view of large-scale precipitation variability. Journal of Climate 6, 1495–1522.

Sahlu, D., Moges, S.A., Nikolopoulos, E.I., Anagnostou, E.N., Hailu, D., 2017. Evaluation of high-resolution multisatellite and reanalysis rainfall products over East Africa. Advances in Meteorology 2017. doi:10.1155/2017/4957960.

Satgé, F., Ruelland, D., Bonnet, M.P., Molina, J., Pillco, R., 2019. Consistency of satellite-based precipitation products in space and over time

807 compared with gauge observations and snow-hydrological modelling in the
808 Lake Titicaca region. Hydrology and Earth System Sciences 23, 595–619.
809 doi:10.5194/hess-23-595-2019.

810 Schellander, H., Lieb, A., Hell, T., 2019. Error structure of metastatistical
811 and generalized extreme value distributions for modeling extreme rainfall
812 in austria. Earth and Space Science 6, 1616–1632.

813 Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., Ziese,
814 M., 2011. GPCC full data reanalysis version 6.0 at 0.5°: Monthly land-
815 surface precipitation from rain-gauges built on GTS-based and historic
816 data. doi:10.5676/DWD_GPCC/FD_M_V6_050.

817 Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M.,
818 Rudolf, B., 2014. GPCC's new land surface precipitation climatology
819 based on quality-controlled in situ data and its role in quantifying the
820 global water cycle. Theoretical and Applied Climatology 115, 15–40.
821 doi:10.1007/s00704-013-0860-x.

822 Serinaldi, F., Kilsby, C.G., 2014. Rainfall extremes: Toward reconciliation
823 after the battle of distributions. Water Resources Research 50, 336–352.
824 doi:10.1002/2013WR014211.

825 Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., Hsu, K., 2018.
826 A review of global precipitation data sets: Data sources, estimation,
827 and intercomparisons. Review of Geophysics 56, 79–107. doi:10.1002/
828 2017RG000574.

829 UNSIDR, 2015. Sendai Framework for Disaster Risk Reduction 2015 - 2030.
830 Technical Report. URL: www.unisdr.org/we/inform/publications/
831 43291.

832 Ushio, T., Sasashige, K., Kubota, T., Shige, S., Okamoto, K., Aonashi, K.,
833 Inoue, T., Takahashi, N., Iguchi, T., Kachi, M., Oki, R., Morimoto, T.,
834 Kawasaki, Z.I., 2009. A kalman filter approach to the Global Satellite
835 Mapping of Precipitation (GSMaP) from combined passive microwave and
836 infrared radiometric data. Journal of the Meteorological Society of Japan
837 87 A, 137–151. doi:10.2151/jmsj.87A.137.

838 Villarini, G., Smith, J.A., Lynn, M., Vitolo, R., Stephenson, D.B., Krajew-
839 ski, W.F., 2011. On the frequency of heavy rainfall for the Midwest of

the United States. Journal of Hydrology 400, 103–120. doi:10.1016/j.jhydrol.2011.01.027.

Ward, P.J., Kummu, M., Lall, U., 2016. Flood frequencies and durations and their response to El Niño Southern Oscillation: Global analysis. Journal of Hydrology 539, 358–378. doi:10.1016/j.jhydrol.2016.05.045.

Wasko, C., Sharma, A., Johnson, F., 2015. Does storm duration modulate the extreme precipitation-temperature scaling relationship? Geophysical Research Letters 42, 8783–8790. doi:10.1002/2015GL066274.

Westra, S., Alexander, L.V., Zwiers, F.W., 2013. Global increasing trends in annual maximum daily precipitation. Journal of Climate 26, 3904–3918. doi:10.1175/JCLI-D-12-00502.1.

Wilson, P.S., Toumi, R., 2005. A fundamental probability distribution for heavy rainfall. Geophysical Research Letters 32. doi:10.1029/2005GL022465.

Zhang, D., Liu, X., Bai, P., Li, X.H., 2019. Suitability of satellite-based precipitation products for water balance simulations using multiple observations in a humid catchment. Remote Sensing 11. doi:10.3390/rs11020151.

Zorzetto, E., Botter, G., Marani, M., 2016. On the emergence of rainfall extremes from ordinary events. Geophysical Research Letters 43, 8076–8082. doi:10.1002/2016GL069445.

Zorzetto, E., Marani, M., 2019. Downscaling of rainfall extremes from satellite observations. Water Resources Research 55, 156–174. doi:10.1029/2018WR022950.

Zorzetto, E., Marani, M., 2020. Extreme value metastatistical analysis of remotely sensed rainfall in ungauged areas: Spatial downscaling and error modelling. Advances in Water Resources 135, 103483. doi:10.1016/j.advwatres.2019.103483.