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# The Probability Distribution of Daily Precipitation at the Point and Catchment Scales in the United States

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**Abstract:** Choosing a probability distribution to represent daily precipitation depths is important for precipitation frequency analysis, stochastic precipitation modeling and in climate trend assessments. Early studies identified the 2-parameter Gamma (G2) distribution as a suitable distribution for wet-day precipitation based on traditional goodness of fit tests. Here, probability plot correlation coefficients and L-moment diagrams are used to examine distributional alternatives for the full-record and wet-day series of daily precipitation at the point and catchment scales in the United States. Importantly, the G2 distribution performs poorly in comparison to either the Pearson Type-III (P3) or Kappa (KAP) distributions. The analysis indicates that the P3 distribution fits the full record of daily precipitation at both the point and catchment scales remarkably well; while the KAP distribution best describes the distribution of wet-day precipitation at the point scale, and the performance of KAP and P3 distributions is comparable for wet-day precipitation at the catchment scale.

**Key Words:** Climate; Rainfall; Weather; L-moment diagram; PPCC; Pearson type III; Kappa; Gamma; Wet-day; Frequency analysis; Trend detection; Stochastic weather models

## 1. Introduction

Establishing a probability distribution that provides a good fit to daily precipitation depths has long been a topic interest in the fields of hydrology, meteorology, and others. The investigations into the daily precipitation distribution are primarily spread over three main research areas, namely, (1) stochastic precipitation models, (2) frequency analysis of precipitation, and (3) precipitation trends related to global climate change. Table 1 displays a sampling of the literature in these three fields, the particular precipitation series and durations under investigation, and the proposed distributions identified. Table 1 is by no means exhaustive; it only attempts to document the widespread interest in the determination of a suitable distribution for daily precipitation totals for various purposes.

[*Table* 1 *goes here*]

### 1.1 Stochastic precipitation and climate models:

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The first section in Table 1 presents a small portion of the literature related to stochastic precipitation modeling also referred to as stochastic weather modeling. The purpose of such models is not so much to investigate the properties of precipitation, but instead to produce artificially generated precipitation sequences that can be used as inputs to other models to explore the behavior of hydrologic systems (Buishand, 1978;Waymire and Gupta, 1981). A wide range of types of stochastic precipitation generators exist as evidenced from review articles Waymire and Gupta (1981), Wilks and Wilby (1999), Srikanthan and McMahon (2001) and Chen and Brissette (2014). Also see the introduction of Mehrotra et al. (2006) for a nice review.

Since our central goal is to select a suitable generalized probability distribution for modeling daily precipitation depths, we are only concerned with the class of "two-part" stochastic daily precipitation models that utilize a probability distribution function to describe precipitation amounts on wet-days, while precipitation occurrence is separately described using a Markov model or some form of a stochastic renewal process (Buishand, 1978;Geng et al., 1986;Waymire and Gupta, 1981;Watterson, 2005).

It is evident from Table 1 that the wet-day precipitation series is virtually the only daily precipitation series that is even considered in the stochastic precipitation model literature. Thom's (1951) suggestion of the 2-parameter Gamma (G2) distribution function for wet-day amounts seems to carry considerable weight. Following the suggestion of numerous previous authors, both Watterson and Dix (2003) and Watterson (2005) assumed a Gamma distribution for wet-day rainfall in the development of stochastic rainfall models.. Buishand (1978) lent support to the suggestion of the Gamma distribution by showing that for the wet-day series at six stations, the empirical Coefficient of Variation to Coefficient of Skewness ratio was quite close to the theoretical value of two for a Gamma distribution.

Geng et al. (1986) used a simple regression to show that the beta parameter of the Gamma distribution for a given month can be predicted reasonably well by the average rainfall per wet-day in that month. Geng et al. (1986) also provided a good review of other literature supporting the use of the Gamma distribution for modeling wet-day rainfall.

While the G2 distribution is by far the most preferred distribution for wet-day precipitation amounts, other distributions have also been suggested. Woolhiser and Roldan (1982) and Wilks (1998) both suggested the use of a three-parameter mixed exponential distribution instead of G2. The three-parameter exponential distribution can describe wet-day amounts by mixing two distinct exponential distributions (each with its own mean parameter) with a parameter that chooses which one to use. Through a variety of goodness of fit tests and log-likelihood analyses, the mixed exponential is shown as being preferred to G2 (Wilks, 1998).

The Weibull (W2) and to a lesser extent the exponential distribution have also been suggested for modeling daily precipitation amounts (Duan et al., 1995;Burgueno et al., 2005). Duan et al. (1995) used a Chi-squared test to demonstrate that synthetic rainfall generated from the Weibull and Gamma (with parameters estimated by method of moments) models best matches the observed data within each month. Separate models were created for each calendar month. (Burgueno et al., 2005) used graphical methods and the Kolmogorov-Smirnov test to give support to the W2 and exponential distributions.

## 1.2 Precipitation frequency analysis:

The second section of Table 1 displays a small portion of the literature related to precipitation frequency analyses. Extreme values of rainfall are of particular interest to urban planners, engineers and hydrologists working on problems related to storm drainage, flooding, and other natural hazards such as precipitation-induced slope failures (landslides). Precipitation frequency analyses are one way to generate the necessary precipitation totals at given return period for hydraulic design purposes. A key step in frequency analysis of precipitation involves selection of a suitable distribution for representing precipitation depths to investigate the extremes. While these analyses can be conducted for multiple precipitation durations, we focus on those that investigate the 1-day duration.

As the extreme rainfall values are of primary importance in these studies, a highly censored series of rainfall is often useful in these analyses. The Annual Maximum Series (AMS) and Partial Duration Series (PDS) are often used in hydrologic frequency investigations (Stedinger et al., 1993). Table 1 displays that many of the precipitation frequency investigations of daily precipitation depths have selected the AMS series. The wet-day series is actually a PDS with zeros and values lower than the detection limit of the instrument (i.e., “trace” values) censored.

In perhaps the most comprehensive assessment of the distribution of precipitation extremes, Papalexiou and Koutsoyiannis (2013) examined the goodness-of-fit of the GEV distribution to a global dataset of AMS at 15,137 sites with lengths varying from 40 to 163 years. Analysis of such a large dataset enabled them to conclude that GEV models of AMS series of daily precipitation provide a good approximation with the shape parameter depending critically upon both the location and length of the series under consideration. Interestingly, when record length and location are taken into account, the shape parameter appears to exhibit a relatively narrow range of small positive values.

For many years, the most common approach to summarizing precipitation frequency analyses in the United States was the work of Hershfield (1961), which is commonly referred to as TP-40. Hershfield (1961) fitted a Gumbel distribution to the AMS series of 24-hour precipitation. More recently investigators have completed these types of analyses by using the method of L-moments and other methods that are more powerful than the traditional goodness of fit measures. In the context of a national revision to the TP-40 rainfall frequency atlas and after the application of L-moment goodness-of-fit evaluations, Bonnin et al., (2006) fitted a generalized extreme value (GEV) distribution to the AMS of rainfall.

Bonnin et al. (2006) performed a very comprehensive national assessment of precipitation frequency by applying the most up-to-date developments in regional frequency analysis to series of annual maximum n-minute precipitation. Using both at-site and regional L-moment goodness-of-fit results, climatic considerations and sensitivity testing, the GEV distribution was selected to best represent the underlying distributions of all daily and hourly AMS rainfall data. GEV was also selected for the 5-, 10-, and 15-minute AMS rainfall data. Naghavi and Yu (1995) also chose the GEV for a

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Hydrology and Earth System Sciences
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study of rainfall extremes in Louisiana. Similarly, Lee and Maeng (2003) selected the GEV and the generalized logistic distributions based on L-moment analysis of 58 stations in Korea.

While the results of Bonnin et al. (2006) apply to the United States, other authors have found similar results using similar methods in other parts of the world. Pilon et al. (1991) used L-moment goodness-of-fit results to show that the Gumbel distribution should be rejected in the favor of the GEV in Ontario, Canada. In Korea, Park and Jung (2002) successfully used the Kappa distribution (of which the GEV is a special case) to generate extreme precipitation quantile maps using both Maximum Likelihood Estimators (MLE) and L-moment estimators (L-ME) for Kappa parameter estimation. They found convergence failure at some stations for the L-ME, and lack of fit for those series fit with MLEs when sample size was too small.

Interestingly, while a great deal of attention is given to fitting distributions to the relatively short AMS series of precipitation depths, very few studies directly explore the probability distribution of the complete series of daily precipitation (including zeros) or the wet-day series of daily precipitation (zeros excluded). Shoji and Kitaura (2006) investigated both full-record and wet-day daily precipitation series, but included only the normal, lognormal, exponential, and Weibull distributions as candidate distributions, and did not employ modern regional hydrologic methods such as the method of L-moments.

Perhaps the most thorough investigations, to date, on the probability distribution of daily precipitation amounts are the global studies by Papalexiou and Koutsoyiannis (2012, 2016). Papalexiou and Koutsoyiannis (2012) derived a generalized Gamma distribution (GG) from Entropy theory, using plausible constraints for wet-day series of daily precipitation series. Together, the two studies by Papalexiou and Koutsoyiannis (2012, 2016) revealed that the GG distribution provides a good approximation to the behavior of observed L-moments of global series of wet-day daily precipitation at 11,519 and 14,157 stations, respectively.

Deidda and Puliga (2006) investigated the degree of left-censoring of wet-day series needed to fit a Generalized Pareto (GPA) distribution for 200 stations in Sardinia, Italy with a range of modern statistical analysis techniques. The “failure-to-reject” goodness-of-fit method was used to establish an optimal threshold for left censoring at each station to make the observed data fit a GPA distribution. Often, Deidda and Puliga (2006) found that no optimal threshold for left censoring could make the data fit a GPA distribution at 5 and 10% confidence intervals. Deidda and Puliga (2006) remarked that data rounding off may explain some of the lack of fit, but their results still leave room for debate on the most likely candidate distribution for daily precipitation.

## 1.3 Precipitation trends and changes:

The third section of Table 1 summarizes a small portion of the precipitation trend literature which has become a rather large area of inquiry due to concerns over climate change, as evidenced from recent reviews on the subject (Easterling et al., 2000;Trenberth, 2011;Madsen et al., 2014). Interestingly, within the literature devoted to detection of changes in precipitation patterns, we find a reliance on previous studies of the probability distribution of daily precipitation for evaluating changes in distributional parameters and in selecting candidate distributions. Almost universally, the G2 distribution appears to be accepted without serious consideration of alternative distributions. For instance, (Groisman et al., 1999) wrote simply, "It is widely recognized that the distribution of daily precipitation totals, P, can be approximated by the Gamma distribution." That is not to say the G2 distribution is not tested for its fit to the observed data. For instance, (Groisman et al., 1999) compared maps of the empirical probability of summer 1-day rainfall exceeding 50.4 mm with maps of probabilities determined by a stochastic model using the fitted G2 distribution for the amounts. They found acceptable fits in regions where there are enough observed daily rainfall events greater than 50.4 mm.

This is an interesting contrast to the precipitation frequency analysis literature where a Gamma distribution is often fit to wet-day series for the purpose of examining extreme rainfalls instead of using the AMS series fitted by a GEV or other distribution. Yoo et al. (2005) explained that conventional frequency analysis (using AMS) cannot expect to predict precipitation changes resulting from climate change; while an examination of the differences in the Gamma distribution's parameters (fitted to the whole wet-day record) might predict such changes. They found that modifying the parameters of the daily Gamma distribution can explain changes in rainfall quantiles predicted by General Circulation Models (GCM) under various climate change scenarios. Wilby and Wigley (2002) plotted the expected 100-year changes in the shape and scale parameter of the G2 distribution according to two GCM models' predictions.

In a national study of precipitation trends, Karl and Knight (1998) employed the G2 distribution to fill in missing precipitation observations. Karl and Knight (1998) wrote that "To determine if precipitation occurs on any missing day, a random number generator is used such that the probability of precipitation is set equal to the empirical probability of precipitation during that month. If precipitation occurs, then the gamma distribution is used to determine the amount that falls for that day, again using a random number generator." Both Watterson and Dix (2003) and Watterson (2005) assumed a G2 distribution for daily precipitation in the development of stochastic rainfall models for use in evaluating changes in precipitation extremes.

We conclude from this brief review that both the precipitation trend and climate change literature have widely used the G2 distribution as a powerful tool to examine not only the possible changes in precipitation patterns, but also the relative rate of change in a geospatial context through mapping. In summary, there are a wide variety of previous studies which have explored the probability distribution of daily precipitation for the purposes of precipitation frequency analysis, stochastic precipitation modeling and for trend detection. There seems to be a consensus that annual maxima appear to be well approximated by either a GEV, Gumbel or Gamma probability density function (pdf) and that series of wet-day daily precipitation totals are well approximated by a Gamma Generalized Gamma, or in some cases a mixed exponential pdf. However, other than the two recent global studies by Papalexiou and Koutsoyiannis (2012, 2016). We are unaware of any studies that have used recent developments in regional hydrologic frequency analysis such as L-moment diagrams or probability plot goodness of fit evaluations to evaluate the probability distribution of the *complete series* of daily precipitation.

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The recent studies by Papalexiou and Koutsoyiannis (2012, 2016) represent perhaps the most comprehensive studies to date, however, they only consider wet-day series of daily precipitation and their L-moment evaluations only evaluate the relationship between L-Skewness and L-Cv, thus they were unable to fully evaluate the goodness-of-fit of the several relatively new three-parameter pdfs introduced in their studies such as the generalized Gamma (GG) and the generalized Burr type XII (GB) pdfs which would require construction of L-Kurtosis versus L-Skew diagrams. Analogous to those two studies, this paper uses several large scale national datasets to re-examine the question of which of the commonly used continuous distribution functions which are widely used in the fields of hydrology, meteorology and climate best fit both wet-day and complete series of observed daily precipitation data.

Instead of considering the GG distribution, the pdf recommended by both Papalexiou and Koutsoyiannis (2012, 2016), which is only suited to wet-day series, has seen very limited use and for which analytical and/or polynomial relationships for L-Kurtosis are unavailable as they are for most commonly used pdfs in hydrology, we consider the more widely used 3 parameter generalization of the Gamma distribution known as the Pearson type III (P3) distribution. Once analytical and polynomial L-moment relationships and parameter estimation methods become available for the GG distribution, future studies should compare the P3 and GG distributions on wet-day series, because on the basis of this study, and Papalexiou and Koutsoyiannis (2016), the P3 and GG distributions appear to have tremendous potential for approximating the distribution of wet-day series.

Our primary objective is to use a very large spatially distributed dataset at both the point and catchment scales, to determine a suitable probability distribution of full-record series and wet-day series of daily precipitation using L-moment diagrams and probability plot correlation coefficient goodness of fit statistics. Analogous to the recent study by Papalexiou and Koutsoyiannis (2016), these evaluations yield very different conclusions than previous research on this subject.

## 2. Study area and data

Precipitation depths at the point and catchment scales are important information in hydrology, meteorology, and other fields, thus our study focuses on both of them. For point precipitation, we employ a data set comprised of daily precipitation depths at 237 first-order NOAA stations from 49 U.S. states (Hawaii is excluded due to fundamentally different precipitation behavior). Station locations are shown in Figure 1a. In contrast, the areal average precipitation for 305 catchments in the international Model Parameter Estimation Experiment (MOPEX) data set (Duan et al., 2006) is also selected for analysis. The catchment locations and boundaries are shown in Figure 1b. The data were quality controlled to remove null values. When greater than 6 null values occurred in a given year or greater than 3 in a given month, the full year of data was removed. When fewer than these numbers of null values were present, they were treated as zeroes. The average record length for point precipitation depths for the 237 sites is 24,657 days (67.5 years). The distribution of record lengths corresponding to the 237 first-order NOAA stations is shown in Figure 2. The MOPEX data set consists of 56 years of areal average

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Hydrology and Earth System Sciences
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Discussions

precipitation from 1948 to 2003, corresponding to a fixed record length 20,454 days for each of the 305 catchments shown in Figure 1b.

[*Figure* 1 *goes here*]

[*Figure* 2 *goes here*]

In addition to the full-record series of daily precipitation, wet-day series were extracted from both data sets. The wet-day series were constructed by excluding zero and "trace" values (those with less than "0.01" recordable precipitation). Wilks (1990) discussed other ways to treat trace precipitation and left-censored data, but for convenience, they are simply excluded. The mean wet-day record lengths for point and areal average precipitation are 7,219 days (equivalent to nearly 20 years) and 14,043 days (more than 38 years), respectively. The distributions of wet-day record length are shown in Figure 3. As expected, the proportion of wet-days in the areal average precipitation data set is higher than that in the point precipitation data set.

[*Figure* 3 *goes here*]

# 3. Methodology

This section describes the methods of analysis used for assessing the goodness-of-fit of various distributional hypotheses, namely, L-moment diagrams and probability plot correlation coefficients.

## 3.1 L-Moment Diagrams

L-moment diagrams are now a widely accepted approach for evaluating the goodness of fit of alternative distributions to observations. The theory and application of L-moments introduced by Hosking (1990) is now widely available in the literature (Stedinger et al., 1993;Hosking and Wallis, 1997), hence it is not reproduced here.

The distribution of daily precipitation totals is highly skewed due to the large proportion of days with zero precipitation. Higher order conventional moment ratios such as skewness and kurtosis are very sensitive to extreme values and can exhibit enormous downward bias even for extremely large sample sizes (Vogel and Fennessey, 1993) as is the case here. However, L-moment ratios are approximately unbiased in comparison to conventional moment ratios, thus providing a particularly useful tool for investigating the pdf of precipitation series.

L-moment ratio diagrams provide a convenient visual way to view the characteristics of sample data compared to theoretical statistical distributions. The L-moment diagrams: L-Kurtosis ($\tau_4$) vs L-Skew ($\tau_3$) and L-Cv ($\tau_2$) vs L-Skew ($\tau_3$) enable us to compare the goodness of fit of a range of three-parameter, two-parameter, and one-parameter (or special case) distributions. Table 2 displays distributions analyzed by means of the $\tau_4$ vs $\tau_3$ L-moment ratio diagrams.

[*Table* 2 *goes here*]

Table 3 displays distributions analyzed by means of the $\tau_2$ vs $\tau_3$ L-moment ratio diagrams.

[*Table* 3 *goes here*]

L-moment ratio diagrams have been used before to examine the distribution of series of annual maximum precipitation data (Pilon et al., 1991;Park and Jung, 2002;Lee and Maeng, 2003;Papalexiou and Koutsoyiannis, 2013) and left-censored records (Deidda and Puliga, 2006). Other than the two recent global studies by Papalexiou and Koutsoyiannis (2012, 2016) which examined the agreement between empirical and theoretical relationships between L-Cv and L-Skew, this is the only study we are aware of, in which a set of uncensored daily precipitation records have been subjected to such a comprehensive L-moment goodness-of-fit analysis. L-moment estimators were chosen in this study for a variety of reasons: (1) they are easily computed and nicely summarized by Hosking and Wallis (1997) for all the cases considered in this study, and (2) estimates of L-moments unbiased and estimates of their ratios are nearly unbiased, and thus for the extremely large sample sizes considered here, sampling variability of empirical L-moment ratios will be extremely small especially when contrasted to distributional choice comparisons.

### 3.2 Probability plot correlation coefficient goodness-of-fit evaluation

Probability plots are constructed for each of the full record and wet-day series using L-moment estimators of the distribution parameters (see Hosking and Wallis (1997)) for the distributions indicated in Table 4.

[*Table* 4 *goes here*]

The goodness of fit of each probability plot is summarized using a probability plot correlation coefficient (PPCC, or simply, r). The PPCC statistic has a maximum value of 1. The PPCC has been shown to be a powerful statistic for evaluating the goodness-of-fit of a very wide range of alternative distributional hypotheses (Stedinger et al., 1993) and for performing hypothesis tests of various two parameter distributional alternatives.

To construct a probability plot and to estimate a probability plot correlation coefficient, requires estimation of a plotting position. There are two classes of plotting positions, those that yield unbiased exceedance probabilities and those that yield unbiased quantile estimates. The Weibull plotting position given by $p=i/(n+1)$ yields an unbiased estimate of exceedance probability regardless of the underlying distribution (see (Stedinger et al., 1993)). Alternatively there would be a unique plotting position to use for each probability distribution, and it is now well known that unbiased plotting positions for three parameter distributions require an additional parameter to estimate within the plotting position. For example, Vogel and McMartin (1991) derived an unbiased plotting position for the P3 distribution which depends upon the skewness of the distribution, a parameter which adds so much additional uncertainty to the analysis that led Vogel and McMartin (1991), after considerable analysis, to not recommend its use. To put all the distributional alternatives on the same footing, we chose to use the Weibull plotting position for estimation of all PPCC values.

## 4. Results and analysis

### 4.1 L-Moment Diagrams

#### 4.1.1 L-Cv vs L-Skew

Figure 4 displays empirical and theoretical distributional relationships between L-Cv and L-Skew for point values of daily precipitation (Figure 4a) and areal average values of daily precipitation (Figure 4b). The various curves represent the theoretical relationship between L-Cv and L-Skew for the distributions indicated. Each plotted point represents the empirical relationship between L-Cv and L-Skew for a single precipitation station or catchment. By comparing the empirically derived points with the theoretical curves, it is possible to see the degree to which the statistical character of the data record matches those of the candidate distributions. We emphasize again, that the sample sizes are large enough in this study so that one may, approximately, ignore sampling variability in all L-moment diagrams. This phenomenon was nicely illustrated in Figure 2 of Blum et al. (2017) for record lengths similar to those used here, but corresponding to daily streamflow records.

The empirical L-moment ratios corresponding to the full-record and wet-day point precipitation series fall within completely different regions in Figure 4a, which is due to the fact that the full-record point precipitation series contain a very large number of zero observations. In contrast, there are much fewer zero observations in the catchment full-record precipitation series thus the empirical L-moment ratios corresponding to the full-record and wet-day catchment precipitation series overlap roughly 50% of the time as shown in Figure 4b.

Both Figure 4a and Figure 4b illustrate a nearly linear relationship between the L-Skew and L-Cv for the two types of full record series. Importantly, these two lines of points, however, do not fall along any of the theoretical curves, demonstrating that the 2-parameter Gamma distribution cannot describe the tail behavior of full-record series of precipitation as has often been assumed in the past.

[*Figure* 4 *goes here*]

In Figure 4a, the wet-day series' points fall primarily within a region bounded by the G2 and GP2 theoretical curves, with the W2 passing through some of the points. In Figure 4b, the wet-day series' points fall primarily in the upper region of the W2 theoretical curve, with the G2 passing through some of the points. These patterns do not indicate a clearly preferred distribution, especially considering that the large sample sizes associated with these series result in negligible sampling variability. Blum et al. (2017, Figure 2) used L-moment diagrams for complete series of daily streamflow observations to demonstrate that the sampling variability in L-moment ratios is negligible for the sample sizes considered in this study. Thus, the scatter shown in Figure 4 is likely due to real distributional differences rather than due to sampling variability as is often the case when one constructs L-moment diagrams for short AMS precipitation records.

### 4.1.2 L-Kurtosis vs L-Skew

Figure 5 displays empirical and theoretical distributional relationships between L-Kurtosis vs L-Skew point values of daily precipitation (Figure 5a) and areal average values of daily precipitation (Figure 5b). The plotted points for the two full record series follow a linear relationship approximately, but the relationships are remarkably similar to the theoretical curve for the Pearson Type-III (P3) distribution. In fact, the P3 pdf seems to be the only 3-parameter distribution that could possibly fit the full record data. It is worth noting that the overall lower bound of L-Kurtosis for all distributions falls below but quite close to the P3 curve at high L-Skew values in Figure 5.

[*Figure* 5 *goes here*]

The estimated L-moment ratios of the wet-day series of point precipitation in Figure 5a reveal more scatter on the plot than for the corresponding full-record series. In this case, the closest theoretical curve to the wet-day points is also the P3 distribution, but the fit is less striking for the wet-day series than for the corresponding full record series. In Figure 5b, the L-moment ratios of the wet-day series of areal average precipitation shows less scatter than for the corresponding full record series and in this case of areal rainfall the P3 theoretical curve passes through most of the points for both the full and wet-day series. Though the fit of the wet-day series to P3 is less striking than for the full record series, the L-moment ratio estimates occupy a space that can be well represented by the Kappa distribution, which occupies not a curve, but a region of the L-Kurtosis vs L-Skew diagram as shown in Figure A1 of Hosking and Wallis (1997). See Hosking (1994) and Hosking and Wallis (1997, Appendix A10) for a complete description of the 4-parameter Kappa distribution.

## 4.2 PPCC

### 4.2.1 Standard boxplots of PPCC

The L-moment diagrams successfully identify two potential candidate distributions for representing the full-record and wet-day daily precipitation series at the point and catchment scales. The PPCC statistic offers another quantitative method for comparing the goodness of fit of different distributions to the daily precipitation observations. Tables 5 and 6 summarize the central tendency and spread of the values of PPCC for each of the distributions for both the full-record and wet-day series of point and catchment scale daily precipitation, respectively. The highest values for the mean, median, 95$^{th}$ percentile, and 5$^{th}$ percentile of the PPCC are shown in bold type. The lowest values of the sample standard deviation of the PPCC values, denoted $\hat{s}$, are also shown in bold. Figure 6 illustrates box-plots of the values of PPCC for distributions fitted to the full-record and wet-day series of daily precipitation data at the point scale. Figure 7 shows box-plots of PPCC values for distributions fitted to the full-record and wet-day precipitation series at the catchment scale.

[*Table* 5 *goes here*]

[*Table* 6 *goes here*]

[*Figure* 6 *goes here*]

[*Figure* 7 *goes here*]

Figure 6 and Table 5 indicate that for the full-record series of point daily precipitation depths, only the G2, P3, and KAP distributions perform well. On the other hand, for the wet-day series of point daily precipitation, all the distributions have median PPCCs well above 0.9. The same situation appears in the areal average precipitation shown in Figure 7 and Table 6, except that the median PPCCs of the remaining four distributions for the wet-day series are significantly lower than the corresponding values for point precipitation.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
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Discussion started: 1 March 2018


The insets in Figures 6 and 7 show detailed views of the boxplots of PPCC values for the G2, P3, and KAP distributions for point and areal average daily precipitation. Both types of precipitation data shows the same results that the P3 is the best performing distribution on average for the full-record series, but the KAP distribution shows the highest PPCCs on average for the wet-day series.

### 4.2.2 Graphical comparison of P3, G2, and KAP

Across all previous comparison, the P3, G2, and KAP are the most likely distributions for describing daily precipitation at the point or catchment scales. The insets in Figures 6 and 7 identify the distributions that exhibit the best fit to the observed series. However, these inserts do not indicate by how much the best performing distribution outperforms the second or third best. For this purpose, pairwise comparisons of the PPCC values of two highly performing distributions for all the stations and catchments are instructive. A simple graphical method can accomplish this goal.

Figure 8a and Figure 8b compare the PPCC values of the P3 (vertical axis) and G2 (horizontal axis) distributions for the full-record and wet-day series of point daily precipitation, respectively. Approximately 98% of stations are displayed on both figures; the remaining stations lie outside the plot domains. Points lying above the diagonal line indicate that the P3 distribution has a higher PPCC for that particular station, and points lying below the diagonal line indicate the G2 results in a higher PPCC. The full-record plot (Figure 8a) shows that in nearly every case, the P3 distribution outperforms the G2 distribution. When the G2 does outperform the P3, the PPCCs are both very high and nearly equal. The wet-day plot shows that the P3 distribution performs significantly better than the G2 distribution in many cases. Thus, we conclude the P3 distribution better represents wet-day daily point precipitation than the more commonly used G2 distribution, in nearly every case.

[*Figure* 8 *goes here*]

Figures 8c and Figure 8d compare the PPCC values of P3 and G2 for the full record series and wet-day series of areal average precipitation, respectively. The results are nearly the same as for the point precipitation in the sense that most points are above the diagonal line; while for a few catchments whenG2 does outperform P3, the points lie on the dividing line, showing only very slight superiority.

Figure 9a and Figure 9b display similar plots comparing the KAP (vertical axis) and P3 (horizontal axis) distribution, for the full-record and wet-day series of point precipitation, respectively. For the full-record series the P3 distribution outperforms the KAP distribution with most of the points lying below the dividing line; whereas, for the wet-day series, the KAP distribution outperforms the P3 distribution for a majority of sites.

[*Figure* 9 *goes here*]

The same conclusion can be obtained for the full-record series of areal average precipitation in Figures 9c except that the better distribution does not dominate, with only 63% points have higher PPCC for P3 distributions. For the wet-day series of areal average precipitation in Figures 9d, the performance of KAP distribution is comparable with that of P3 distribution with almost the same number of points lying in each region.

It is somewhat surprising that the 3-parameter P3 distribution outperforms the 4-parameter KAP distribution because the extra information contained in the 4th parameter (essentially a second shape parameter in the case of the Kappa distribution) would be expected to lead to a better goodness-of-fit. The L-moment diagram (Figure 5), however, shows that the fit of the full record data to the P3 theoretical curve is so good that a 4th parameter could be extraneous. Additionally, it should be noted that the pattern of the full record stations or watersheds on the L-Kurtosis vs L-Skew plot approaches the overall lower bound for all distributions, a place where the Kappa distribution parameter estimates may become less accurate. The "h" shape parameter, for example, approaches infinity in this region (see Hosking and Wallis (1997, Figure A1)).

## 5. Conclusions

This study has demonstrated that L-moment diagrams and probability plot correlation coefficient goodness of fit evaluations can provide new insight into the distribution of very long series of daily precipitation at both the point and catchment scales. Though the commonly used 2-parameter Gamma distribution performs fairly well on the basis of traditional goodness-of-fit tests, L-moment diagrams and probability plot correlation coefficient goodness of fit evaluations reveal that very long series of uncensored daily point and areal average precipitation are better approximated by a Pearson-III distribution and importantly, they do not resemble any of the other commonly used distributions.

We conclude that for representing uncensored, full record daily precipitation at the point and catchment scales, the 3-parameter Pearson-III distribution performs remarkably well. For cases in which only wet-day precipitation amounts are required, the Pearson-III distribution is comparable with the 4-parameter Kappa distribution for the areal average precipitation; when the point precipitation is of concern, the Kappa distribution should be the distribution of choice. We also conclude that future investigations should consider comparisons between the generalized Gamma distribution introduced by Papalexiou and Koutsoyiannis (2012, 2016) for wet-day daily precipitation and both the Pearson type III and Kappa distributions recommended here.

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## Table captions:

**Table 1:** Review of literature pertinent to daily precipitation probability distribution selection.

**Table 2:** Table 2: Theoretical probability distributions presented on the L-Kurtosis vs L-Skew L-moment diagram. *Italicized distributions are special cases of other distributions*.

**Table 3:** Theoretical probability distributions presented on the L-Cv vs L-Skew L-moment diagram.

**Table 4:** Distributions used in probability plot goodness of fit evaluations.
**Table 5:** Central tendency and spread of values of PPCC for the 237 precipitation stations.

**Table 6:** Central tendency and spread of values of PPCC for the 305 areal average precipitation catchments.

## Figure captions:

**Figure 1:** Map showing locations of a) 237 precipitation gaging stations, and b) 305 catchments.

**Figure 2:** Distribution of full record length of point precipitation base on weather stations.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 1 March 2018



**Figure 3:** Distribution of wet-day record length: a) point precipitation; and b) areal average precipitation over watersheds. Days with zero precipitation are removed in the wet-day records

**Figure 4:** L-Cv vs L-Skew L-moment ratio diagram of sample L-moments and theoretical distributions: a) point precipitation; and b) areal average precipitation depths.

**Figure 5:** L-Skew vs L-Kurtosis L-moment ratio diagram of sample L-moments and theoretical distributions: a) point precipitation; and b) areal average precipitation depths. Logistic (L), Normal (N), Uniform (U), Gumbel (G), and Exponential (E) distributions appear as a single point.

**Figure 6:** Standard boxplots of r for all 7 distributions evaluated for a) full record, and b) wet-day series of point precipitation depths.

**Figure 7:** Standard boxplots of r for all 7 distributions evaluated for a) full- record, and b) wet-day series of areal average precipitation depths.

**Figure 8:** Comparison of PPCC (r) values for the P3 (vertical axis) and G2 (horizontal axis) distributions for the a) point precipitation depths' full -record, b) point precipitation depths' wet-day, c) areal average precipitation depths' full-record, and d) areal average precipitation depths' wet-day series. Points lying above the line represent stations with a higher r for the P3 distribution than G2 distribution.

**Figure 9:** Comparison of r values for P3 (horizontal axis) and KAP (vertical axis) distributions for the a) point precipitation depths' full-record, b) point precipitation depths' wet-day, c) areal average precipitation depths' full-record, and d) areal average precipitation depths' wet-day series.

# Tables

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 1 March 2018


Hydrology and Earth System Sciences
Discussions
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**Table 1:** Review of literature pertinent to daily precipitation probability distribution selection.

*1. Stochastic Precipitation Modelling:*

| Author | Year | Stations | Series type | Duration | Distribution | Justification |
|---|---|---|---|---|---|---|
| Thom | 1951 | | Wet-day | 1-day | Gamma | |
| Buishand | 1978 | 6 | Wet-day | 1-day | Gamma | Cv-Cs ratio |
| Geng et al | 1986 | 6 | Wet-day, by month | 1-day, monthly | Gamma | Regress. fit: β vs mean wet-day depth |
| Woolhiser and Roldan | 1982 | | Wet-day | 1-day | Mixed Exponential | MLE, Akaike Information Criterion |
| Duan et al | 1995 | 1 | Wet-day, by month | 1-day | Calib. W2, Gamma | MLE, Chi-sq test |
| Wilks | 1998 | 25 | Wet-day | 1-day | Mixed Exponential | MLE, goodness of fit |
| Waterson and Dix | 2003 | | Wet-day | 1-day | Gamma | Literature |
| Burgueno et al | 2005 | 75 | Wet-day | 1-day | Exponential, Weibull | Normalized Rainfall Curve |
| Waterson | 2005 | | Wet-day | 1-day | Gamma | Literature |

*2. Precipitation Frequency Analysis*

| Author | Year | Stations | Series type | Duration | Distribution | Justification |
|---|---|---|---|---|---|---|
| Hershfield (TP-40) | 1962 | | AMS | 24 hour | Gumbel | |
| Pilon et al | 1991 | 75 | AMS | 5 min - 24 hour | GEV | L-moments |
| Naghavi & Yu | 1995 | 25 | AMS | 1-24 hour | GEV | L-moments, PWMs, Monte Carlo experiments |
| Park and Jung | 2002 | 61 | AMS | 1, 2-day | Kappa(4) | |
| Lee and Maeng | 2003 | 38 | AMS | 1-day | GEV, GLO | L-moments |
| Bonnin et al | 2006 | | AMS | 5 min - 24 hour | GEV | L-moments |
| Shoji and Kitaura | 2006 | 243 | Complete, Wet-day | Hour, Day, Month, Year | Lognormal, Weibull | Goodness of fit |
| Deidda and Puliga | 2006 | 200 | Left Censored Wet-day PDS | 1-day | Generalized Pareto | "Failure-to-reject" method, L-moments |
| Papalexiou and Koutsoyiannis | 2012 | 11,519 | Wet-Day | 1-day | Generalized Gamma | L-moments |
| Papalexiou and Koutsoyiannis | 2013 | 15,137 | AMS | 1-day | GEV | L-moments |
| Papalexiou and Koutsoyiannis, | 2016 | 14,157 | Wet-Day, by month | 1-day | Generalized Gamma and Burr type XII | L-moments and Goodness-of-fit |

*3. Precipitation Trends and Climate Change*

| Author | Year | Stations | Series type | Duration | Distribution | Justification |
|---|---|---|---|---|---|---|
| Waggoner | 1989 | 55 | Monthly | 1-month | Gamma | Literature Review |
| Groisman et al | 1999 | 1313 | Summer (wet-day) | 1-day | Gamma | Literature Review, goodness of fit to |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | extreme rainfall quantiles |
| Wilby and Wigley | 2002 | GCM | Seasonal | 1-day | Gamma | Literature Review |
| Yoo et al | 2005 | 31 | Monthly (wet-day) | 1-day | Gamma | Literature Review |
| Watterson | 2005 | GCM | January, July | 1-month (daily forced) | Gamma | Literature Review |

**Table 2:** Theoretical probability distributions presented on the L-Kurtosis vs L-Skew L-moment diagram. *Italicized distributions are special cases of other distributions.*

| Distribution | Abbreviation | Parameters |
|---|---|---|
| Generalized Extreme Value Type III | GEV | 3 |
| Generalized Logistic | GLO | 3 |
| Generalized Pareto | GPA | 3 |
| Lognormal | LN3 | 3 |
| Pearson Type III | P3 | 3 |
| *Exponential* | E | 2 |
| *Gumbel* | G | 2 |
| *Normal* | N | 2 |
| *Logistic* | L | 2 |
| *Uniform* | U | 1 |

**Table 3:** Theoretical probability distributions presented on the L-Cv vs L-Skew L-moment diagram.

| Distribution | Abbreviation | Parameters |
|---|---|---|
| Gamma | G2 | 2 |
| Generalized Pareto | GP2 | 2 |
| Lognormal | LN2 | 2 |
| Weibull | W2 | 2 |

**Table 4:** Distributions used in probability plot goodness of fit evaluations.

| Distribution | Abbreviation | Parameters |
|---|---|---|
| Generalized Extreme Value Type III | GEV | 3 |
| Generalized Logistic | GLO | 3 |
| Generalized Pareto | GPA | 3 |
| Lognormal | LN3 | 3 |
| Pearson Type III | P3 | 3 |
| Gamma | G2 | 2 |
| Kappa | KAP | 4 |

**Table 5:** Central tendency and spread of values of PPCC for the 237 precipitation stations.

| Distribution | Full Record | | | *Percentiles* | | Wet Day | | | *Percentiles* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | $\hat{s}$ | 95th | 5th | Mean | Median | $\hat{s}$ | 95th | 5th |
| P3 | **0.9953** | **0.9962** | **0.0045** | **0.9991** | **0.9892** | 0.9952 | 0.9971 | 0.0063 | 0.9995 | 0.9872 |
| GEV | 0.5949 | 0.5928 | 0.0527 | 0.6755 | 0.5166 | 0.9338 | 0.9375 | 0.0222 | 0.9609 | 0.8944 |
| GPA | 0.6192 | 0.6177 | 0.0604 | 0.7145 | 0.5339 | 0.9793 | 0.9828 | 0.0145 | 0.9949 | 0.9500 |
| GLO | 0.5939 | 0.5922 | 0.0509 | 0.6708 | 0.5172 | 0.9115 | 0.9154 | 0.0235 | 0.9423 | 0.8734 |
| LN3 | 0.7975 | 0.8078 | 0.0545 | 0.8731 | 0.7055 | 0.9838 | 0.9855 | 0.0075 | 0.9924 | 0.9727 |
| G2 | 0.9945 | 0.9954 | 0.0046 | 0.9988 | 0.9876 | 0.9925 | 0.9949 | 0.0079 | 0.9990 | 0.9789 |
| KAP | 0.9780 | 0.9784 | 0.0137 | 0.9926 | 0.9644 | **0.9971** | **0.9985** | **0.0048** | **0.9997** | **0.9915** |

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 1 March 2018


Hydrology and Earth System Sciences
Discussions
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**Table 6:** Central tendency and spread of values of PPCC for the 305 areal average precipitation catchments.

| Distribution | **Full Record** | | | *Percentiles* | | **Wet Day** | | | *Percentiles* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Median** | $\hat{s}$ | **95th** | **5th** | **Mean** | **Median** | $\hat{s}$ | **95th** | **5th** |
| P3 | **0.9972** | **0.9975** | **0.0023** | 0.9993 | **0.9941** | **0.9977** | 0.9985 | **0.0028** | 0.9996 | **0.9936** |
| GEV | 0.6757 | 0.6706 | 0.0666 | 0.8014 | 0.5836 | 0.8003 | 0.7965 | 0.0474 | 0.8917 | 0.7264 |
| GPA | 0.7247 | 0.7177 | 0.0795 | 0.8711 | 0.6140 | 0.8688 | 0.8687 | 0.0484 | 0.9586 | 0.7894 |
| GLO | 0.6654 | 0.6607 | 0.0608 | 0.7772 | 0.5803 | 0.7800 | 0.7750 | 0.0441 | 0.8669 | 0.7101 |
| LN3 | 0.8717 | 0.8736 | 0.0444 | 0.9409 | 0.8035 | 0.9362 | 0.9373 | 0.0224 | 0.9737 | 0.8983 |
| G2 | 0.9967 | 0.9971 | 0.0024 | 0.9992 | 0.9935 | 0.9974 | 0.9985 | 0.0034 | 0.9996 | 0.9924 |
| KAP | 0.9959 | 0.9968 | 0.0034 | **0.9996** | 0.9898 | 0.9976 | **0.9987** | 0.0026 | **0.9998** | 0.9929 |

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 1 March 2018


# Figures

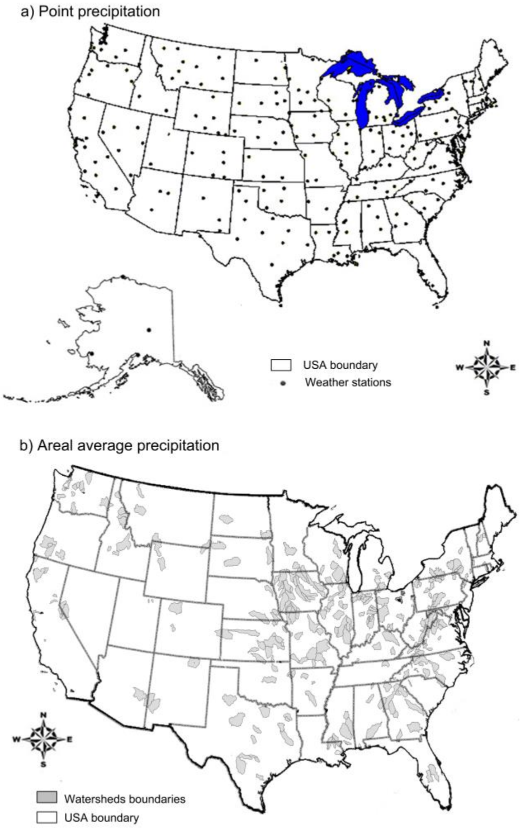



**Figure 1:** Map showing locations of a) 237 point precipitation gaging stations, and b) 305 MOPEX catchments.

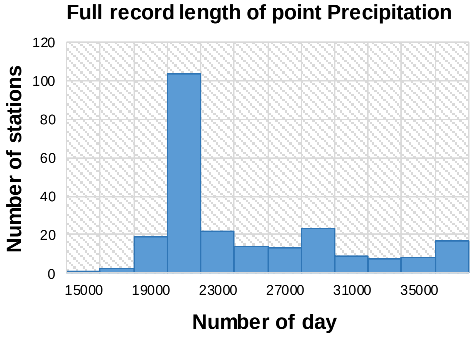



**Figure 2:** Distribution of length of records of point daily precipitation data for the 237 gaging stations depicted in Figure 1a.

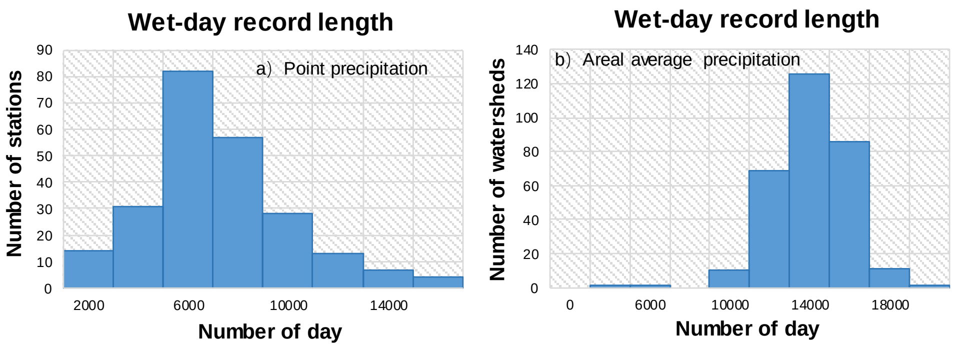
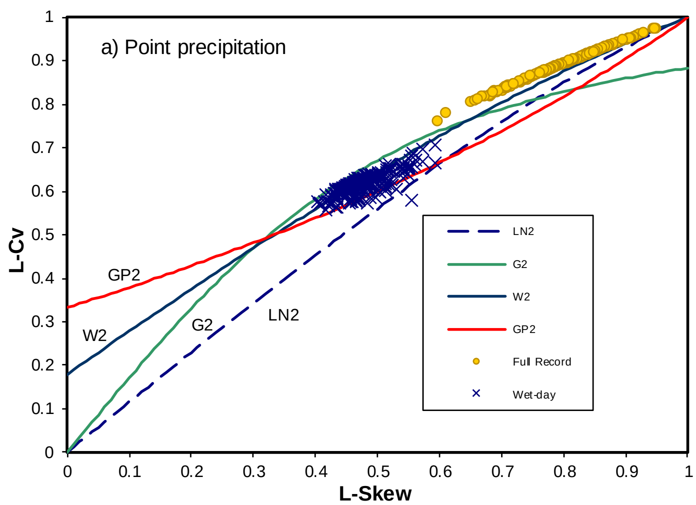



**Figure 3:** Distribution of wet-day record lengths corresponding to the two datasets: a) point precipitation; and b) areal average precipitation over catchments. Days with zero precipitation are removed in the wet-day records



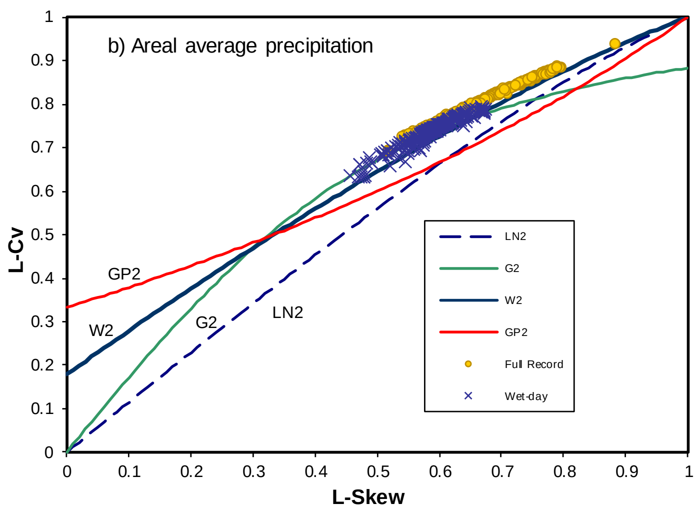
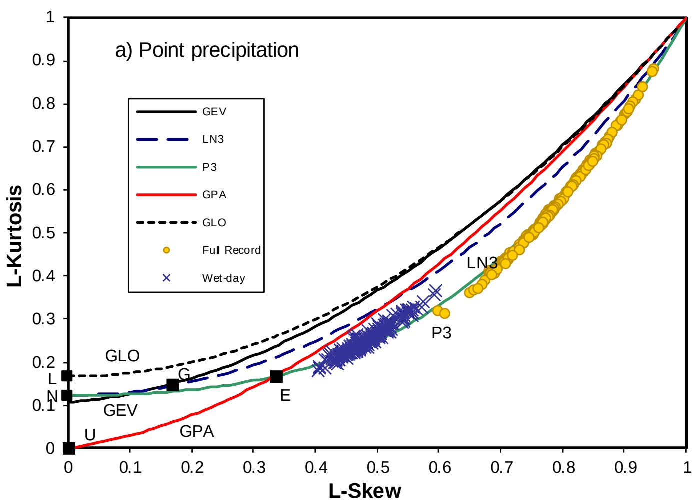
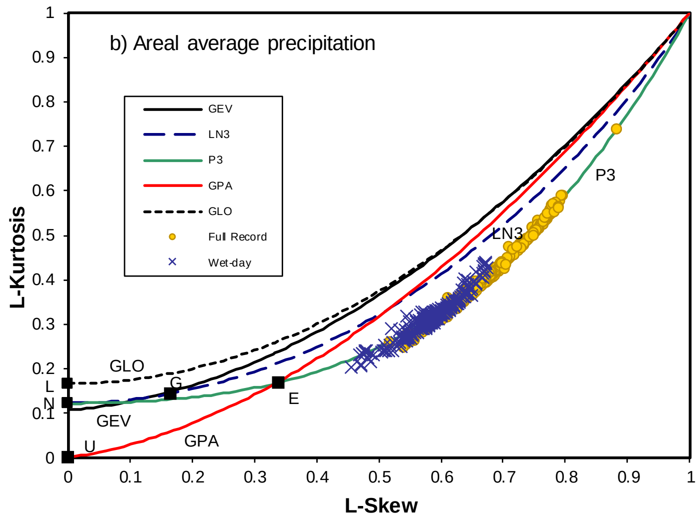



**Figure 4:** L-Cv vs L-Skew L-moment ratio diagram of sample L-moments and theoretical distributions for: a) point daily precipitation; and b) areal average daily precipitation depths.



Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 1 March 2018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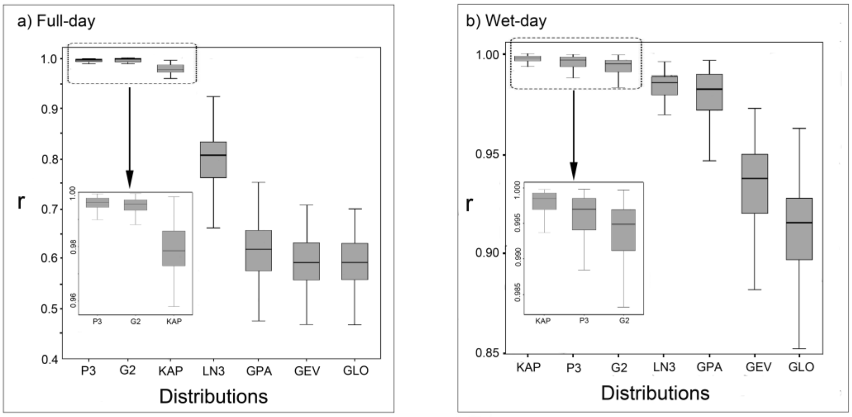


**Figure 6:** Standard boxplots of r for all 7 distributions evaluated for a) full record, and b) wet-day series of point precipitation depths.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-85
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 1 March 2018




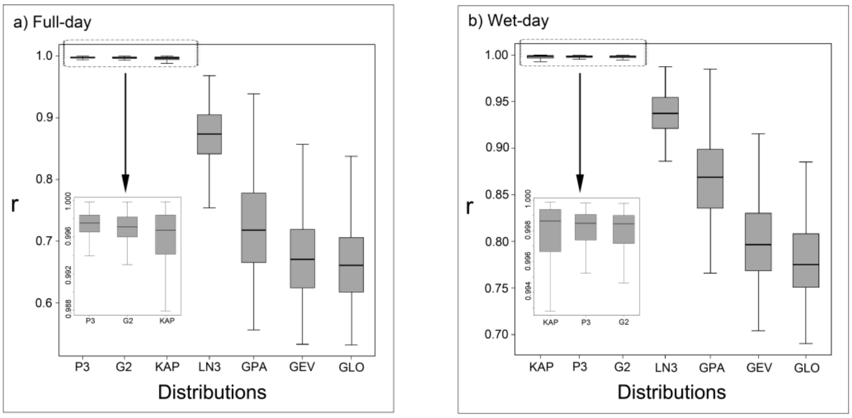


**Figure 7:** Standard boxplots of r for all 7 distributions evaluated for a) full- record, and b) wet-day series of areal average precipitation depths.

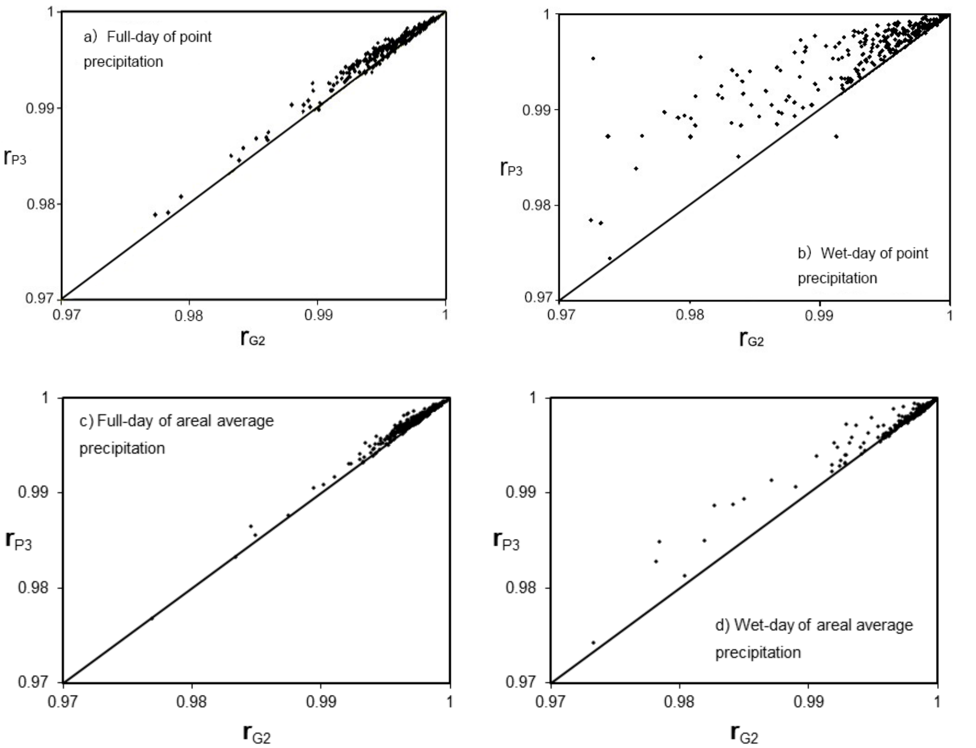


**Figure 8:** Comparison of PPCC (r) values for the P3 (vertical axis) and G2 (horizontal axis) distributions for the a) point precipitation depths' full -record, b) point precipitation depths' wet-day, c) areal average precipitation depths' full-record, and d) areal average precipitation depths' wet-day series. Points lying above the line represent stations with a higher r for the P3 distribution than G2 distribution.

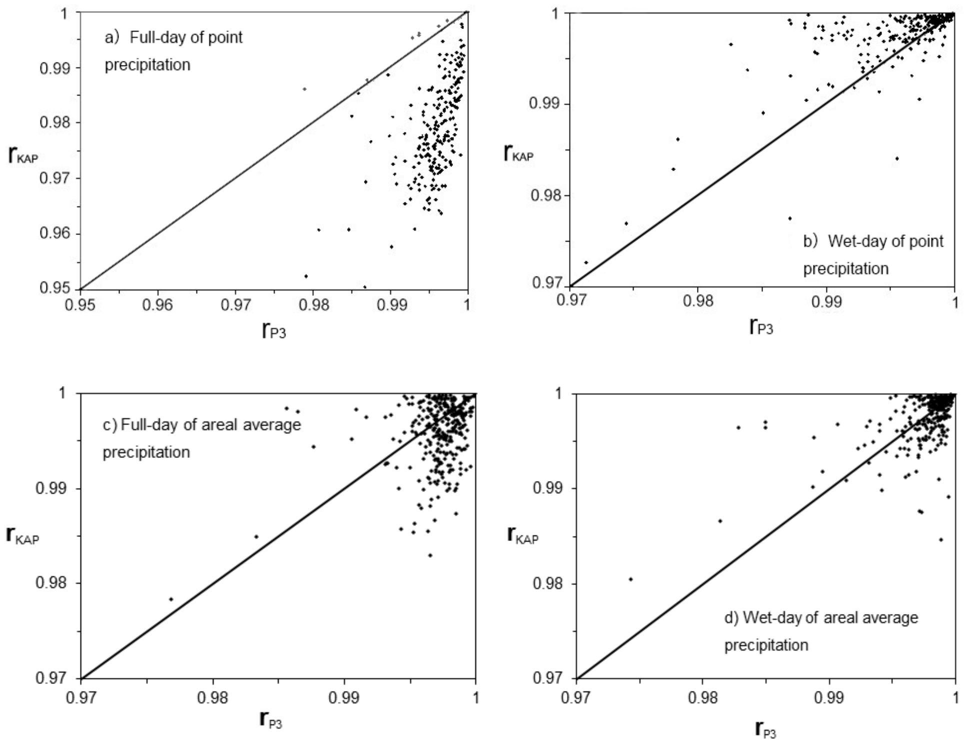


**Figure 9:** Comparison of r values for P3 (horizontal axis) and KAP (vertical axis) distributions for the a) point precipitation depths' full-record, b) point precipitation depths' wet-day, c) areal average precipitation depths' full-record, and d) areal average precipitation depths' wet-day series.