

S1. Methods for parameter estimation in one- and two-parameter probability distributions.

One- and two-parameter distributions were designated to serve as a reference point for evaluating overparameterization and overfitting in more complex models. For this task, the exponential (Exp) and two-lognormal (2LN) distributions were selected.

The Exp was used in the research of Balbi and Lallemand (2023), Ekanayake and Cruise (1993), Willems et al. (2009). The PDF function is given in equation (S1):

$$f(x) = \lambda e^{-\lambda x}, \text{ for } x \geq 0 \quad (\text{S1})$$

where:

λ is the rate.

The estimation of the parameters and fitting of Exp distribution was done using the following R packages: 'stats'.

The 2LN was used in the research of Kuczera (1982), Willems et al., (2007), Cassalho et al. (2018), The PDF function is given in equation (S2):

$$f(x) = \frac{1}{\sqrt{2\pi\sigma x}} e^{\frac{-(\log(x)-\mu)^2}{2\sigma^2}}, \quad (\text{S2})$$

where: μ and σ are the mean and standard deviation of the logarithm, respectively.

The estimation of the parameters and fitting of 2LN distribution was done using the following R packages: 'stats'.

S2. The goodness-of-fit assessment for one- and two-parameter distributions.

The goodness of fit was assessed using MAE or RMSE accuracy measures and CRPS (for details see subsection 3.4) between two distributions: Exp I LN2. Additionally, both distributions (Exp and LN2) were evaluated against three- and four-parameter distributions (P3, LN3, GEV and GGEV) using the same criteria.

S3. Random distributions

Random distributions were generated for the GEV, GGEV, LN2, and Exp distributions. Using the 'MCMCExtreme' R package, we used random generation from the GGEV distribution: `rggev` to create random samples of the GGEV distribution (Do Nascimento and Moura E Silva, 2015). Sample size (n) corresponded to the empirical sample size (N). We used the parameters (μ, σ, ξ, δ) determined for the theoretical GGEV distribution. Of course, we did this only for the best-fit samples to the GGEV distribution (281 samples). Next, we obtained new data series, which we called random series.

Using the 'evd' package, we generated random samples from the GEV distribution using the function `rgev` (Stephenson, 2024). The sample size (n) was based on the empirical sample size

(N). We applied the parameters (μ, σ, ξ) that were determined for the theoretical GEV distribution. This process was conducted exclusively for the 172 best-fit samples to the GEV distribution. Subsequently, we created new data series, which we referred to as random series.

Using the 'stats' package (functions `rlnorm` and `rexp`), random distributions were generated based on the parameters of the theoretical LN2 and Exp distributions (R Core Team, 2022).

The `set.seed` (123) was used for generated random samples so that the results could be reproduced.

Table S1. The count of four fitting distributions (3P, LN3, GEV, GGEV) using mean absolute error, root mean square error and continuous ranked probability score, categorized by types of trends

Goodness of fit distribution	Mann Kendall trend test	P3	LN3	GEV	GGEV	Sum
Mean absolute error	No trend (<i>NMT</i>)	96	61	111	178	446
Mean absolute error	Negative trend (<i>NT</i>)	32	27	53	88	200
Mean absolute error	Positive trend (<i>PT</i>)	4	5	8	15	32
	Sum	132	93	172	281	678

Explanation to the table: P3 – Pearson type III distribution, LN3 – 3-parameters log-normal distribution, GEV - Generalized extreme value distribution, GGEV - the Dual Gamma Generalized Extreme Value Distribution

Table S2. Probability distributions (P3, LN3, GEV, GGEV) for samples classified by catchment area ranges: micro-catchments (0-10 km²), meso-catchments (10-100 km²), macro-catchments (100-1,000 km²), large catchments (1,000-10,000 km²), very large catchments (>10,000 km²).

Catchment area	P3	LN3	GEV	GGEV	Total
Monotonic trend (<i>NMT</i>)					
<10	0	0	2	0	2
10-100	9	8	20	11	48
100-1,000	46	30	62	120	258
1,000-10,000	31	17	18	39	105
>10,000	10	6	9	6	32
Negative trend (<i>NT</i>)					
<10	0	0	0	0	0
10-100	1	2	3	2	8
100-1,000	14	14	31	50	109
1,000-10,000	13	7	15	27	62
>10,000	4	4	3	7	18
Positive trend (<i>PT</i>)					
<10	0	0	0	0	0
10-100	1	1	3	6	11
100-1,000	3	4	4	7	18
1,000-10,000	0	0	1	2	3
>10,000	0	0	0	0	0

Explanation to the table: P3 – Pearson type III distribution, LN3 – 3-parameters log-normal distribution, GEV - Generalized extreme value distribution, GGEV - the Dual Gamma Generalized Extreme Value Distribution

Table S3. Basic characteristics of catchment area size (A) and peak flow (Qp) for descriptive no trend (NMT) samples with determined probability distributions

No.	Distribution of probability	Trend detection	A [km ²]		Qp [m ³ /s]	
			Min	Max	Min	Max
1	3P3	NMT	33	193,666	1.94	6,950
2	LN3	NMT	36	109,775	8.64	6,160
3	GEV	NMT	3.6	168,239	1.64	6,980
4	GGEV	NMT	50	68,216	2.18	6,000

Table S4. Basic characteristics of catchment area size (A) and peak flow (Qp) for descriptive negative trend (NT) samples with determined probability distributions

No.	Distribution of probability	Trend detection	A [km ²]		Qp [m ³ /s]	
			Min	Max	Min	Max
1	3P3	NT	58	32 092	6.08	972
2	LN3	NT	68	30 648	6.56	1480
3	GEV	NT	49	38 395	4.46	2400
4	GGEV	NT	83	180 267	4.97	6890

Table S5. Basic characteristics of catchment area size (A) and peak flow (Qp) for descriptive positive trend (PT) samples with determined probability distributions

No.	Distribution of probability	Trend detection	A [km ²]		Qp [m ³ /s]	
			Min	Max	Min	Max
1	3P3	PT	34	583	10.7	464
2	LN3	PT	96	376	29.4	371
3	GEV	PT	48	2 470	4.55	235
4	GGEV	PT	35	1 480	8.29	780

References

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