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Combining elicited prior with new observations improves frequency estimates of rare rainfall events

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The selection of exceedance probabilities for rainfall extremes depends on the importance of the infrastructure and the consequences of its failure. Estimating quantiles of short-duration rainfall extremes is challenging due to the limited length of available instrumental records, especially in the region of very low probabilities. Bayesian approaches have been proposed as an alternative to classical frequency methods, as they allow the incorporation of additional sources of information through prior distributions, thereby improving inference from relatively short data series. The aim of this study is to improve the estimation of quantiles of short-duration rainfall extremes (15 and 30-minute durations) focusing on the region of low probabilities, by combining modern observations from the Hurbanovo station (1966–2009) with expert-derived historical quantiles from the period 1901–1965 within a Bayesian framework. The goal of this study is to demonstrate how incorporating expert information as prior knowledge can supplement the relatively short instrumental record and reduce the uncertainty of extreme rainfall quantile estimates, particularly for low annual exceedance probabilities (p~0.01). The results indicate that the width of the credible intervals for these quantiles is substantially reduced when additional expert knowledge is incorporated into the prior.

KEY WORDS: rainfall, extremes, quantiles, Bayesian inference, elicitation, expert knowledge, Hurbanovo

Introduction

In engineering practice, the selection of exceedance probabilities for rainfall extremes depends on the importance of the infrastructure and the consequences of its failure (e.g. WMO, 2009; ECS, 2004). While flood-protection structures are typically designed for events with low exceedance probabilities (e.g. $p = 0.01$), extremely rare rainfall events are associated with even lower exceedance probabilities ($p \leq 0.01$), corresponding to return periods of hundreds to thousands of years (Koutsoyiannis, et al., 1998; Salas, et al., 2014). Because observed rainfall records are usually too short, the estimation of such low-probability extremes is inherently uncertain (Markovič and Faško; 2025; Coles, 2001; Katz et al., 2002). Bayesian approaches have been proposed as an alternative to classical frequency analyses, as they enable the incorporation of additional sources of information through prior distributions, thereby improving inference from relatively short data series (Viglione et al., 2013; Gaume et al., 2010; Merz and Blöschl, 2008; Coles and Tawn, 1996; Davison and Smith, 1990). The aforementioned studies integrated historical flood information into the likelihood function. An alternative Bayesian approach extends this concept: rather than relying solely on historical rainfall observations, expert estimates of rainfall quantiles are incorporated directly into the prior distribution. In Slovakia, available rainfall records from self-recording (digitalized pluviographs) or automatic rain gauges generally span less than 30 years (Onderka and Pecho; 2023). Consequently, a major source of uncertainty in rainfall frequency analysis arises from the limited length of available data, which affects the estimation of return periods and associated rainfall quantiles. To reduce uncertainties in the estimates of extreme rainfall quantiles corresponding to low probabilities of exceedance (i.e. $p < 0.01$) it is important to combine all relevant information in frequency analysis (Viglione et al., 2013; Merz and Blöschl, 2008). Merz and Blöschl (2008) distinguish three principal options of expanding the information available for frequency analysis: i) temporal expansion, ii) spatial expansion, and iii) causal expansion. Temporal expansion involves incorporating information about extreme events that occurred outside the main observational period, either before or after the instrumental record. While this concept has primarily been applied to flood data in previous studies (e.g., by Gaume et al., 2010; Merz and Blöschl, 2008; Viglione et al., 2013), in this study we apply a similar approach to rainfall frequency analysis.

In the context of rainfall extremes, temporal expansion may include historical information about extreme rainfall events that occurred prior to the systematic observational

period, as well as previously derived estimates of their quantiles (Coles and Tawn, 1996). Spatial expansion, in turn, refers to incorporating information from rainfall extremes observed at nearby gauges within a climatologically homogeneous region, thereby improving the reliability of rainfall frequency estimates at the site of interest. Regional frequency analysis approaches, such as pooling data from climatologically homogeneous regions and applying scaling relationships between rainfall intensity and duration, have been widely adopted (see Hosking and Wallis, 1997; Koutsoyiannis et al., 1998). In addition, recent studies have highlighted the influence of climate variability and climate change on short-duration rainfall extremes, with increasing rainfall intensities observed in several parts of Europe, particularly for convective events (Blöschl et al., 2020). Similar scaling-based approaches have also been successfully applied in Slovakia, where studies have demonstrated the suitability of intensity–duration–frequency (IDF) scaling relationships for improving the estimation of short-duration rainfall extremes under limited data conditions (e.g. Bara, et al. 2010; Bara, et al. 2009; Foldes at al., 2018; Kohnova et al., 2018) These findings further emphasize the need to integrate multiple sources of information, including regional datasets and climate model outputs, into the frequency analysis framework (Westra et al., 2014; Fowler et al., 2021).

The aim of this study is to improve the estimation of quantiles of short-duration rainfall extremes (15 and 30-minute durations) focusing on the region of low probabilities by combining modern observations from the Hurbanovo station (1966–2009) with expert-derived historical quantiles from the period 1901–1965 within a Bayesian framework. The goal of this study is to demonstrate how incorporating expert information as prior knowledge can supplement the short instrumental record and reduce the uncertainty of extreme rainfall quantile estimates, particularly for low annual exceedance probabilities.

Material and methods

Bayesian framework

Within the Bayesian framework the parameters are assumed to be random variables (Coles, 2001). Their distribution can be derived two sources of information (Kirnbauer et al., 1987): i) the information contained in the sample of observations Y and quantified by the likelihood function $L(Y|\theta)$; ii) the second source of information is the a priori probability density function of the model parameters θ, given some prior information. Combining these two kinds of information yields the posterior density function $p(\theta|Y)$.

According to Bayes' theorem, the probability of the parameters θ conditional on the observations $p(\theta|\mathrm{Y})$ is proportional to the prior probability of the parameters θ and to the probability of the observations y conditional on the parameters $L(Y|\theta)$:

$$p(\theta|\mathrm{Y}) = \frac{L(\mathrm{Y}|\theta)\, p(\theta)}{\int_{\Omega} L(\mathrm{Y}|\theta) p(\theta) d\theta}, \quad (1)$$

The prior, $p(\theta)$, as the prior distribution of the model parameters can be specified using external information that is not already contained in the data Y. The integral in the denominator, which is computed on the whole parameter space Ω, serves as the normalization constant to ensure a unit area under the posterior probability density function $p(\theta|\mathrm{Y})$. In most cases, the integral cannot be evaluated analytically (in a closed form), simulations based on Markov chain Monte Carlo techniques are usually deployed. One important aspect of Bayesian inference is that the parameters θ are considered as random parameters and that their uncertainty can be modelled. This allows us to assign credible intervals to the estimated quantiles. Credible intervals are analogues to confidence intervals in frequentists statistics (Viglione et al., 2013).

$$L(Y|\theta) = \prod_{i=1}^{m} p_{GEV}(y_i|\theta), \quad (2)$$

where Y is the sample of annual rainfall maxima $y_i, y_2, y_3, \ldots y_m$ recorded over m years. This represents the likelihood function (AghaKouchak et al., 2013; Coles, 2001; Ragno et al., 2019).

Eliciting prior information from expert information

The prior $p(\theta)$ encapsulates our knowledge about the parameters θ before observing the data Y (Haddad, 2025). In general, we can characterize priors as informative, i.e. based on previous studies or expert judgement, or non-informative designed to have minimum influence (Coles, 2001). The GEV shape parameter ξ controls the behavior of heavy tails influencing the probability of extremes in the upper tail of the distribution (Serinaldi and Kilsby, 2014; Papalexiou and Koutsoyiannis, 2013). In a previous study using the same Hurbanovo station data, Onderka and Pecho (2023) employed an informative prior for the shape parameter (ξ) of the GEV distribution, assuming that ξ falls within a plausible range derived from values reported in the literature. Papalexiou and Koutsoyiannis (2013) analyzed over 15 000 daily rainfall series spanning from 40 up to 163 years, and found that ξ converges to ~0.114 (std ≈ 0.045) for long series, confirming it is positive ($\xi > 0$) for daily rainfall extremes following Fréchet-type GEV rather than the Gumbel distribution (Lutz et al., 2020; Fukutome et al., 2018; Serinaldi and Kilsby, 2014; Huard et al., 2010). The way a prior is chosen critically affects the posterior when data are limited, as is the case with annual maxima of rainfall intensities. To reduce subjectivity in choosing prior distribution for the ξ parameter in GEV distribution Onderka et al. (2022) reviewed literature to support the selection of initial prior values. Ulrich et al. (2021) found that for annual maxima of rainfall with aggregation levels from 1 minute to 120 hours the shape parameter typically ranges from 0 to 0.3. Accordingly, Onderka et al. (2022) chose a prior $\xi \sim N(0.15; 0.075)$, which covers

~95 % of values within the range 0–0.3. The quantile function of the GEV is defines as:

$$q_p = \mu - \frac{\sigma}{\xi}[1 - \{-\log(1-p)^{-\xi}\}]. \quad (3)$$

Coles and Tawn (1996) formulated that for ordered quantiles $q_{p1} < q_{p2} < q_{p3}$, the differences:

$$\bar{q}_1 = q_{p1} - e_1, \quad (4a)$$
$$\bar{q}_2 = q_{p2} - q_{p1}, \quad (4b)$$
$$\bar{q}_3 = q_{p3} - q_{p2}, \quad (4c)$$

can be modeled as independent and gamma distributed: $\bar{q}_i \sim gamma\left(\alpha_{i,}\ \beta_{i,}\right)$, where e_1 is a lowest physically possible value (i.e. $e_1 = 0$ for rainfal). The prior estimates for the gamma parameters $\left(\alpha_{i,}\ \beta_{i,}\right)$ are determined from the location and variability measures of the expert's prior beliefs. Coles and Powell (1996) illustrated this approach with an experiment in which experts were asked to provide estimates of the median and 90% uncertainty for each rainfall quantile; whereas these values were then used to solve for the corresponding gamma parameters. As for the prior distribution, Coles and Tawn (1996) chose the gamma distribution for each $\bar{q}_i$with the probability density function f_i:

$$f_i(x) = \frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} x^{\alpha_i - 1} e^{-\beta_i x} \quad x \in (0, \infty), \quad (5)$$

where $\Gamma(.)$ is the gamma function.

For the prior specification given by Eq. 1, the joint prior for the q_{pi} is obtained as

$$f(q_{p1}, q_{p2}, q_{p3}) \propto q_{p1}^{\alpha_1 - 1} \exp\left(-\beta_1 q_{p1}\right)$$
$$\prod_{i=1}^{3}\left(q_{pi} - q_{pi-1}\right)^{\propto_i - 1} exp\left\{-\beta_i\left(q_{pi} - q_{pi-1}\right)\right\}, \quad (6)$$

Substituting the quantiles (Eq. 3) into Eq. 6 and multiplying by the Jacobian of the transformation, which accounts for the change of distribution from the gamma differences to the GEV parameters, yields the prior in terms of the GEV parameters, and subsequent multiplication by the likelihood gives the posterior.

Posterior inference in extreme value analysis is commonly performed using Markov Chain Monte Carlo (MCMC) sampling (Ragno et al., 2019; AghaKouchak et al., 2013; Coles, 2001; Coles and Tawn, 1996). This approach requires the specification of tuning parameters for the sampling algorithm and produces a dependent sample from the posterior distribution. Convergence must therefore be assessed using diagnostic procedures, typically based on multiple chains started from different initial values, in order to determine whether the chains have converged and which initial samples should be discarded as burn-in.

To incorporate prior information derived from historical quantiles, we used the R package 'revdbayes' (Stephenson, 2016). Unlike standard MCMC sampling, this package implements the generalized ratio-of-uniforms method (Wakefield et al., 1991), as described in detail by Northrop (2017). An advantage of this direct simulation approach is that it generates independent random samples from the posterior distribution, rather than correlated samples produced by MCMC. Although the method still involves tuning parameters, the implementation in 'revdbayes' is designed to determine these automatically. Further details of the ratio-of-uniforms method are provided in the package vignette (Northrop, 2017).

Rainfall measurements at the Hurbanovo station

The Hurbanovo meteorological station was selected because it represents the oldest station in the region with the longest continuous series of instrumental observations. Measurements began in the late nineteenth century, and following its incorporation into the Austro-Hungarian meteorological network in 1901, the station became one of the principal observing sites within the network. In 2020, this station was included in the list of "Centennial Observing Stations" of the World Meteorological Organization (WMO number: 0-20000-0-11858). The rain gauge is located at an elevation of 115 m a.s.l. (latitude 47.8725°, longitude 18.19306°). Although the Hurbanovo station does not exhibit the highest recorded rainfall extremes in Slovakia (Onderka and Pecho, 2023), it provides relatively high-quality, homogeneous, and long-term observations, rendering it particularly suitable for analyzing historical rainfall extremes (Onderka et al., 2022; Onderka et al., 2025). The present study relies exclusively on data from the Hurbanovo station.

The first recording precipitation gauge installed within the territory of present-day Slovakia was the Swiss-manufactured Hottinger weighing pluviograph. In 1900, in order to facilitate more detailed investigations of atmospheric precipitation, the observatory at Hurbanovo was equipped with then new Hellmann-type pluviograph (Hellmann-Fuess), which was a float-type pluviograph with a orifice area of 200 cm². In parallel, a weighing pluviograph (Anderkó–Bogdánfy type), also with a 200 cm² orifice area, was tested in 1899 and operated at the Hurbanovo statin after 1902. Unlike the Hellman-Fuess, the Anderkó–Bogdánfy pluviograph enabled precipitation recording during winter; however, it was less precise, primarily due to its higher sensitivity to wind effects, which led to increased under-catch of wind-driven precipitation. The Hellmann pluviograph was typically used during the warm part of the year, while the Anderkó–Bogdánfy instrument was employed in winter. Later in the twentieth century, the most widespread self-recording pluviograph became the Czechoslovak IBA (Metra IBA) float-type pluviograph with a 250 cm² orifice area. This instrument remains operational at the station until the present day along with a modern automatic rain gauge. A rather detailed description of rain gauges installed at the Hurbanovo station is given in Onderka et al. (2025).

The climatology of precipitation at the Hurbanovo station has been studied since the early years of the station's operation. Early statistical summaries were published

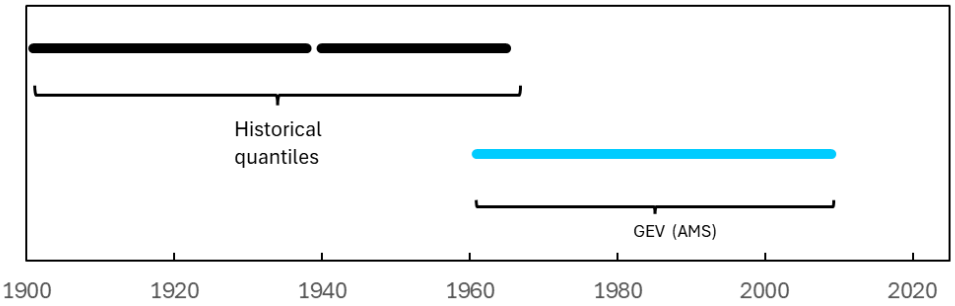


Fig. 1. Sources and temporal coverage of precipitation quantiles and annual maxima series (AMS) used in the analysis. Expert-based quantiles using the historical method of Šamaj and Valovič(1973).

in climatological atlases. In continental climatic conditions, the diurnal cycle of precipitation is strongly influenced by convective processes. Convection occurs most frequently during the summer months and significantly affects the temporal distribution of rainfall within the day.

Historical data analysis

To ensure consistency in the identification of annual maxima between the historical period 1901–1965 and the more recent observations from 1961–2009 (Fig. 1), it was necessary to follow the same methodological framework used in the historical analyses. The dataset covering the period 1961–2009 is based on digitized pluviograph records. Unfortunately, more recent data have not yet been digitized. The expert rainfall quantiles published by Šamaj and Valovič (1973) were derived using a method originally introduced in 1934 (Guidelines for Hydrological Service, 1934). Due to the overlap in years 1961–1965 between the historical and modern periods, the modern period was truncated to 1966–2009. The historical procedure relied on the gradual extraction of rainfall segments from paper pluviograph charts using a moving-window technique. For each duration, rainfall intensities exceeding a predefined threshold were extracted over the entire observation period. The extracted rainfall segments were summarized in frequency tables describing the relative occurrence of rainfall intensities for each duration. These values were plotted on semilogarithmic paper, with probabilities on a logarithmic abscissa and rainfall on the vertical axis; an envelope curve was then drawn above the points to represent the upper bound of observed rainfall intensities. The construction of the envelope curve inherently involved a degree of subjectivity based also on the knowledge of climatology of rainfall extremes. The envelope curve reflects both the empirical data and expert interpretation of the limiting behavior of rainfall intensities. Despite its simplicity and subjective elements, the method retained practical importance for several decades. In Slovakia, results derived from this historical procedure have long served as a benchmark for the design of hydraulic and water-management infrastructure (Šamaj and Valovič; 1973). The period 1901–1965 formed the observational basis of the rainfall frequency analysis in Hurbanovo; unfortunately, the processed series of rainfall maxima are no longer available. Only the paper pluviograph charts have remained archived, while the published tabulated summaries of rainfall frequencies are available in the work of Šamaj and Valovič (1973). Consequently, the original event-level maxima cannot be reanalysed using contemporary extreme-value statistical techniques.

Results and discussion

Example from Hurbanovo

Prior elicitation based on expert-estimated quantiles has the advantage that experts can express their knowledge in terms of observable rainfall amounts associated with specific probabilities or return periods. In contrast, the parameters of a distribution function are abstract quantities that are not directly measurable and are therefore difficult for experts to interpret or assess. Formulating prior information through quantiles thus allows expert knowledge to be incorporated in a more natural way (Coles and Tawns, 1996).

Historical quantiles corresponding to annual exceedance probabilities (AEP) of 0.05, 0.02, and 0.01 were used to define expert-based priors for each quantile estimated from data covering the period 1901–1965 (Table 1). Quantile values for the shorter period 1940–1960 are also shown; these are higher than those for the full 1901–1965 period, suggesting that extreme rainfall events of both 15- and 30-minute durations occurred more frequently and with greater intensity during this interval. This pattern is further supported by analyses of convective instability (CAPE) during the summer season (Fig. 5). CAPE is employed here solely as a proxy for atmospheric conditions favoring intense precipitation from convection (Onderka and Pecho, 2021), although additional processes and atmospheric variables also contribute.

The analyzed dataset comprises 15- and 30-minute rainfall annual maxima measured at the Hurbanovo station between 1961–2009 (Fig. 2).

Effect of sample size on GEV quantiles

To illustrate the influence of record length on extreme rainfall estimates, annual maxima of 15- and 30-minute rainfall totals were analyzed using the Generalized Extreme Value (GEV) distribution. A sliding-window approach was employed to examine the sensitivity of quantile estimates to sample size. Windows of varying lengths were defined. The window was then shifted along the series in one-year increments, generating overlapping sub-series of identical length. For each window, the parameters of the GEV distribution were inferred with maximum likelihood approach (ML). The resulting quantiles for all windows of the same length were aggregated to box-plots, illustrating the stability of the estimates as a function of sample size. In the case of quantiles corresponding to return period of 10-years (upper panel Fig. 3), the interquartile range (IQR) in the boxplots shows the effect of sample size on the total distribution of quantile estimates. For the shortest sampling window (L=10 years) the 10-year quantiles ranged from ~12.8 mm to ~17 mm. With increasing sampling window length L the distribution of quantile estimates tends to decline, whereas at the longest sampling window (L = 30 years) the interquartile range of the box plots shown in Fig. 3 was only ~14.9 mm to ~15.1 mm.

The box-plots highlight that the estimated quantiles depend strongly on the length and position of the record period used. Shorter windows produce noticeable variability particularly for higher return periods, indicating that extreme rainfall estimates can be sensitive to the chosen subset of data. This underscores the importance of using the longest available observational record to reduce sampling variability. These results show that relying on short observational records in frequency analysis can lead to biased or unstable estimates of extreme quantiles, because certain years had weaker rainfall extremes. Such sensitivity demonstrates that short periods may underestimate the true intensity of rare events, potentially affecting infrastructure design or risk assessments.

Temporal clustering of extremes

To visualize the timing of extremes we converted the annual maxima series into binary series using a simple rule:

$$B = \begin{cases} 1 & if\ R_i \geq u \\ 0 & if\ R_i < u, \end{cases}$$

where R_i is annual maximum rainfall observed during an i-th year, u [mm] is a threshold of rainfall annual maxima for which we test the series. Fig. 4 shows the binary series for 15-minute annual maxima series using threshold u corresponding to the 50th, 60th, 70th, 80th and 90th percentiles. The rationale of transforming the original annual maximum series into binary series is to show that rainfall extremes tend to form clusters in time because the background climate state favors or suppresses extreme events. Clustering affects long-term risk assessment by creating periods where historical exceedance probabilities underestimate or overestimate risk, if variability is ignored. During the analyzed period 1961–2009, rainfall annual maxima exceeded the 90th percentile (u=15.5 mm) five times, with two exceedances occurring between 1961–1975 and three exceedances

Table 1. Expert historical quantiles of 15- and 30-minute rainfall (annual exceedance probabilities – AEP) based on observations at the meteorological station in Hurbanovo over the period 1901–1965 (Šamaj and Valovič, 1973). *Values in parentheses at AEP = 0.05 correspond to quantiles derived from a shorter subset period (1940–1960) as published in Šamaj (1968)

AEP [-]	Return period [years]	15-minute rainfall quantile [mm]	30-minute rainfall quantile [mm]
0.05	20	21.1 (*24.4)	25.7 (*31.8)
0.02	50	23.8	29.2
0.01	100	25.2	30.8

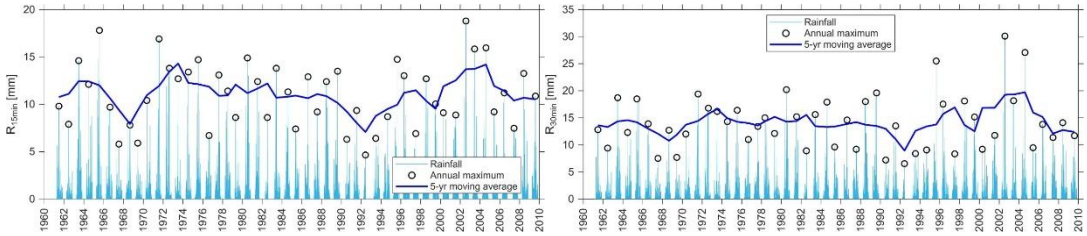


Fig. 2. Annual maximum series of 15-minute rainfall and 30-minute rainfall observed during the period 1961–2009 for which pluviographic data are available. The underlying 5-yearly moving sums for individual rainfall events are also indicated.

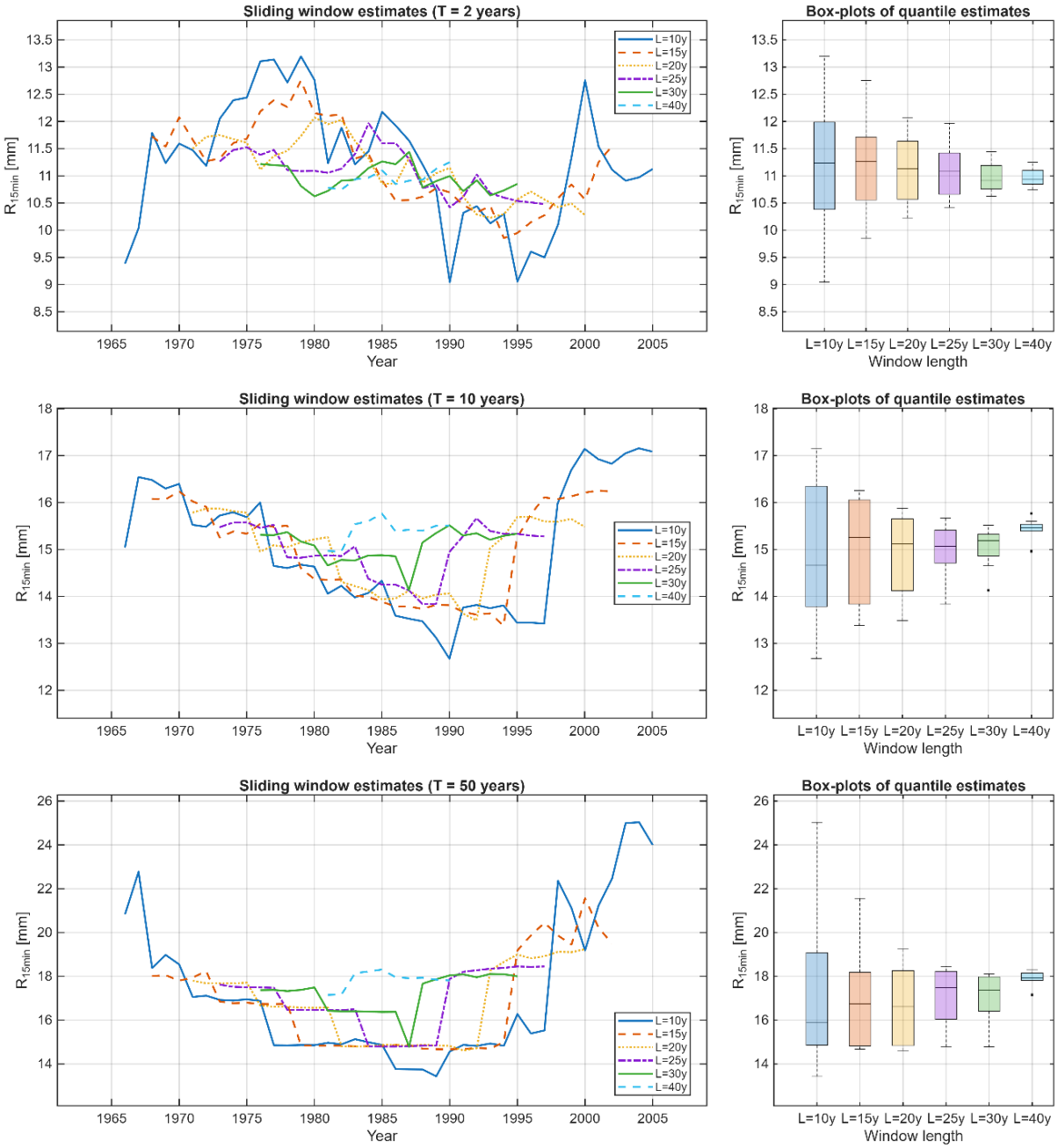


Fig. 3. GEV quantiles of 15-minute rainfall for different return periods (T=2, 10 and 50 years) estimated by fitting GEV distribution (ML) over centered moving windows of varying lengths (L=10, 15, 20, 25, 30, and 40 years). Boxplots show the spread of quantiles estimates for different window lengths L.

occurring between 2000–2009. If we generalize the overall pattern of exceedances above the chosen threshold u, the period from the mid-1970s to the late 1980s appears to have experienced fewer extremes in 15-minute rainfall. For the sake of brevity, Fig. 4 illustrates only the exceedances for the 15-minute rainfall, but the 30-minute rainfall exhibited a similar pattern.

Eliciting historical quantiles

The expert quantiles of 15- and 30-minute rainfall at the Hurbanovo station, estimated for annual exceedance probabilities AEP = 5%, 2% and 1%, are listed in Table 1. These are referred to as the historical quantiles. These were derived by Šamaj and Valovič (1973) using data from the period 1901–1965. The expert judgment involved in determining these historical quantiles primarily concerns how the exceedance curves were constructed. i.e. it is highly subjective process based on personal experience, climatological expertise, rather than a purely data-driven approach. The impact of incorporating historical expert knowledge on the estimation of 15-minute and 30-minute quantiles using the Bayesian framework are shown in Fig. 6 and

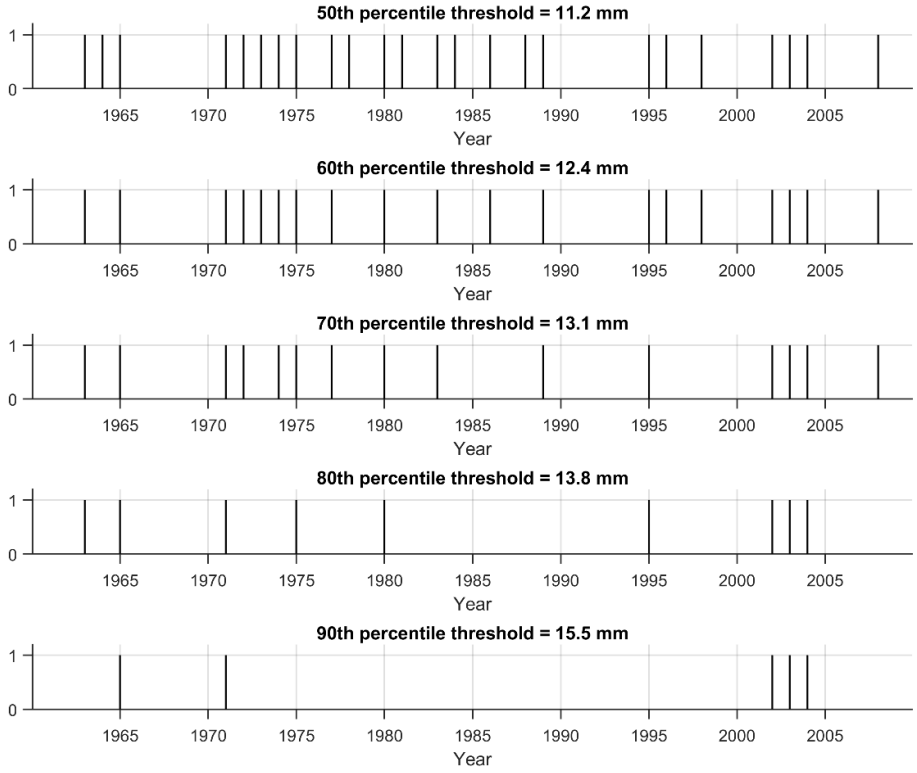


Fig. 4. Binary plots showing the occurrence of 15-minute annual maxima above chosen percentiles corresponding to thresholds u [mm].

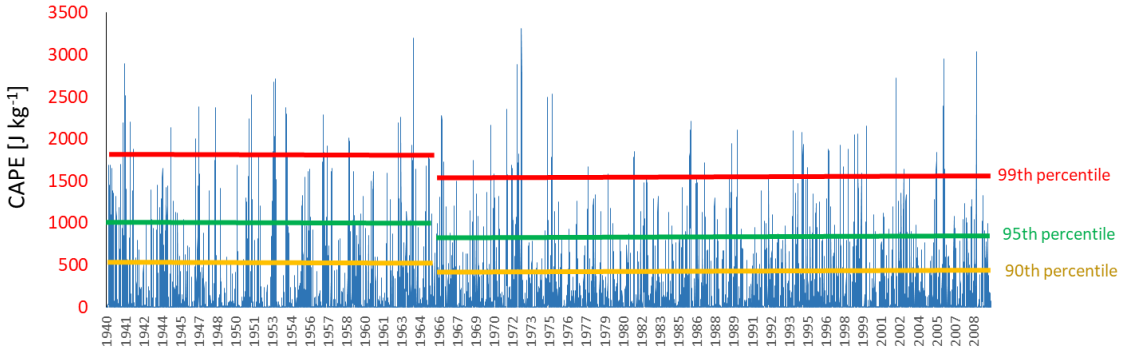


Fig. 5. Convective Available Potential Energy (CAPE) derived from ERA5, downloaded from the Copernicus Climate Data Store. Changes between the periods before and after 1965 are quantified using percentiles. The 1940–1965 period exhibits higher CAPE values, suggesting more favorable conditions for strong convective development compared to the 1966–2009 period. CAPE values were averaged over the four nearest grid points to the Hurbanovo station.

Fig. 7. Tables 2 and 3 show the estimated rainfall quantiles for 15-minute and 30-minute durations, respectively, along with their 90% credible intervals. Simulations using flat prior are included to demonstrate the case in which no expert knowledge is applied (i.e. when the posterior reflects only the observed annual maxima). Results are shown for a flat prior and for expert-derived historical quantiles with varying levels of uncertainty (5%, 10%, 15%, and 20%). For reference, empirical quantiles are plotted as well. This comparison highlights how expert knowledge affects estimates of rare rainfall extremes, particularly in the upper tail of the distribution, and how the posterior increasingly relies on observations as expert uncertainty grows.

The key finding illustrated in Fig. 6 and Fig. 7 is that incorporating historical expert quantiles substantially reduces the uncertainty in simulated rainfall quantiles. To assess sensitivity, we varied the assumed uncertainty in the expert information from 5% to 20% across panels (a)–(d). Even with increasing uncertainty in the prior,

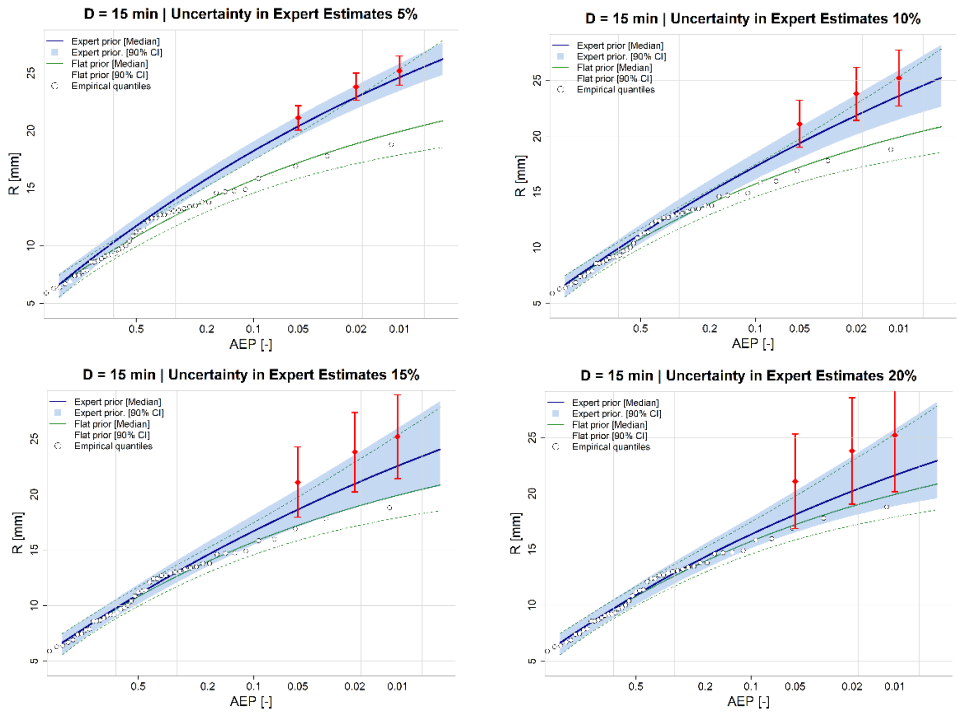


Fig. 6. Quantiles of 15-minute rainfall derived from the Bayesian posterior incorporating historical expert estimates (Table 1). Panels show uncertainty in expert estimates of 5%, 10%, 15%, and 20%. The simulations with flat prior are included to illustrate the case when no expert knowledge is applied, i.e. when only the observed data contribute to the posterior. Empirical estimates are shown using Gringorten plotting position formula.

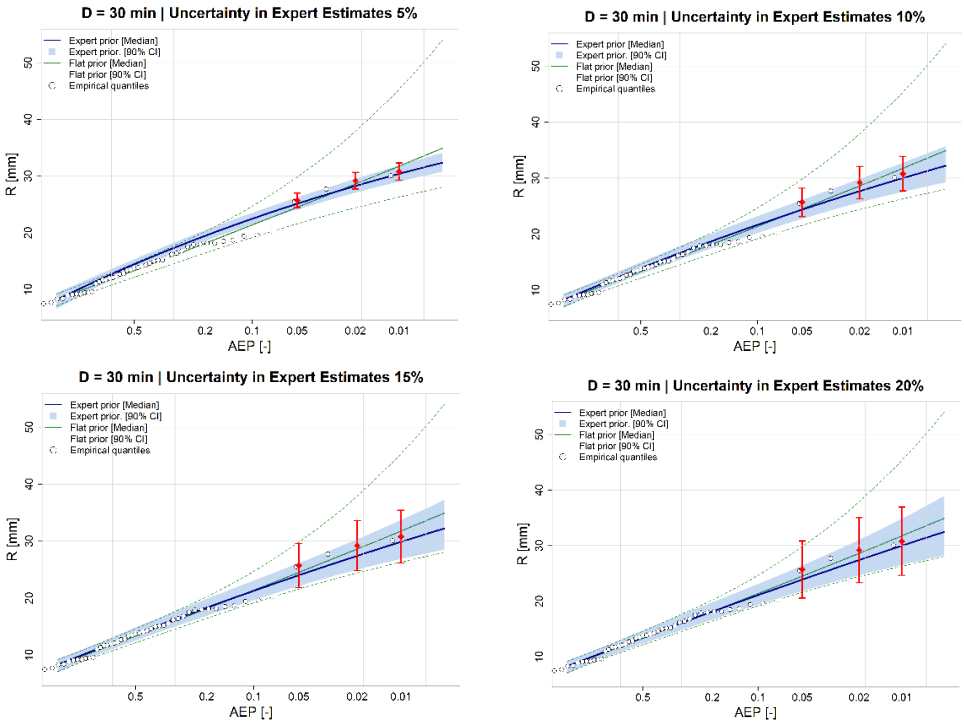


Fig. 7. Quantiles of 30-minute rainfall derived from the Bayesian posterior incorporating historical expert estimates (Table 1). Empirical estimates are shown using Gringorten plotting position formula. Panels show uncertainty in expert estimates of 5%, 10%, 15%, and 20%. The simulations with flat prior are included to illustrate the case when no expert knowledge is applied, i.e. when only the observed data contribute to the posterior.

Table 2. Quantiles of 15-minute rainfall at Hurbanovo for flat prior (i.e. no prior information involved) and expert prior with 90% credible intervals. The uncertainty in expert quantiles is allowed to vary from 5% to 20. The table includes the median quantile estimates (median values) as well as the lower and upper bounds of the 90% credible intervals

Expert uncertainty [%]	AEP [-]	Flat prior (median)	Flat prior (P05)	Flat prior (P95)	Expert prior (median)	Expert prior (P05)	Expert prior (P95)
5	0.5	10.81	9.95	11.69	11.74	11.02	12.45
	0.2	13.96	12.97	15.17	15.81	15.08	16.58
	0.1	15.73	14.58	17.46	18.23	17.44	19.07
	0.05	17.21	15.84	19.75	20.37	19.51	21.27
	0.02	18.86	17.13	22.91	22.9	21.89	23.93
	0.01	19.92	17.9	25.32	24.61	23.45	25.82
10	0.5	10.81	9.95	11.69	11.23	10.39	12.09
	0.2	13.96	12.97	15.17	14.99	13.98	16.07
	0.1	15.73	14.58	17.46	17.29	16.14	18.53
	0.05	17.21	15.84	19.75	19.36	18.02	20.82
	0.02	18.86	17.13	22.91	21.86	20.15	23.72
	0.01	19.92	17.9	25.32	23.61	21.49	25.93
15	0.5	10.81	9.95	11.69	11	10.16	11.91
	0.2	13.96	12.97	15.17	14.56	13.52	15.75
	0.1	15.73	14.58	17.46	16.71	15.48	18.16
	0.05	17.21	15.84	19.75	18.63	17.08	20.47
	0.02	18.86	17.13	22.91	20.95	18.81	23.58
	0.01	19.92	17.9	25.32	22.56	19.88	25.97
20	0.5	10.81	9.95	11.69	10.93	10.07	11.83
	0.2	13.96	12.97	15.17	14.34	13.29	15.53
	0.1	15.73	14.58	17.46	16.35	15.11	17.89
	0.05	17.21	15.84	19.75	18.11	16.53	20.23
	0.02	18.86	17.13	22.91	20.21	18.01	23.33
	0.01	19.92	17.9	25.32	21.63	18.88	25.77

the inclusion of expert knowledge noticeably narrows the credible intervals compared with the case of a flat prior, demonstrating that expert-derived quantiles provide valuable information that stabilizes estimates of rare rainfall extremes. Besides reducing the width of the credible intervals, Fig. 6 shows that the median posterior values shift higher after incorporating expert information compared to the flat prior. This suggests that even higher 15-minute annual maxima might have occurred in the period 1901–1961, so the expert-derived quantiles for this historical period appear higher than those for 1966–2009, which are represented by simulations using the flat prior. This assumption is further supported by the clustering of threshold-exceeding 15-minute extremes of annual maxima at the beginning of systematic observations (Fig. 4). This clearly demonstrates the benefit of using a historically elicited prior, as it incorporates information from data that are no longer available, allowing the posterior to reflect extreme values that would be underestimated if only recent observations and a flat prior were used.

Tables 2 and 3 summarize the estimated rainfall quantiles under different assumptions regarding the uncertainty of expert-derived historical quantiles.

For an annual exceedance probability of $p = 0.01$ and an assumed expert uncertainty of 15%, the median estimate of the 15-minute rainfall under a flat prior is 19.92 mm, with a 90% credible interval of 17.90 to 25.32 mm (Table 2). Incorporating expert-based historical quantiles shifts the median to 22.56 mm, with a corresponding credible interval between 19.88 to 25.97 mm. Consequently, the width of the credible interval decreases from 7.42 mm to 6.09 mm.

A similar pattern is observed for the 30-minute rainfall duration at $p = 0.01$. Under the flat prior (Table 3), the median estimate is 31.76 mm, with credible interval from 26.31 mm to 45.34 mm. After incorporating the expert prior, the median decreases slightly to 29.86 mm, while the credible interval narrows substantially (26.86–33.71 mm). This corresponds to a reduction in interval width from 19.03 mm to 6.85 mm.

Table 3. Quantiles of 30-minute rainfall at Hurbanovo for flat prior (i.e. no prior information involved) and expert prior with 90% credible intervals. The uncertainty in expert quantiles is allowed to vary from 5% to 20%. The table includes the median quantile estimates (median values) as well as the lower and upper bounds of the 90% credible intervals

Expert uncertainty [%]	AEP [-]	Flat prior (median)	Flat prior (P05)	Flat prior (P95)	Expert prior (median)	Expert prior (P05)	Expert prior (P95)
5	0.5	13.32	12.15	14.64	14.44	13.51	15.34
	0.2	18.14	16.42	20.22	19.47	18.55	20.45
	0.1	21.37	19.16	24.68	22.47	21.49	23.52
	0.05	24.5	21.58	29.81	25.12	24.08	26.24
	0.02	28.6	24.42	37.93	28.26	27.07	29.53
	0.01	31.76	26.31	45.34	30.4	29.04	31.86
10	0.5	13.32	12.15	14.64	13.93	12.9	15
	0.2	18.14	16.42	20.22	18.7	17.42	20.07
	0.1	21.37	19.16	24.68	21.66	20.2	23.2
	0.05	24.5	21.58	29.81	24.36	22.72	26.1
	0.02	28.6	24.42	37.93	27.67	25.66	29.86
	0.01	31.76	26.31	45.34	30	27.55	32.75
15	0.5	13.32	12.15	14.64	13.66	12.55	14.82
	0.2	18.14	16.42	20.22	18.31	16.9	19.87
	0.1	21.37	19.16	24.68	21.26	19.63	23.08
	0.05	24.5	21.58	29.81	24	22.12	26.15
	0.02	28.6	24.42	37.93	27.41	24.97	30.33
	0.01	31.76	26.31	45.34	29.86	26.86	33.71
20	0.5	13.32	12.15	14.64	13.51	12.39	14.74
	0.2	18.14	16.42	20.22	18.13	16.67	19.81
	0.1	21.37	19.16	24.68	21.1	19.39	23.11
	0.05	24.5	21.58	29.81	23.89	21.83	26.44
	0.02	28.6	24.42	37.93	27.42	24.66	31.08
	0.01	31.76	26.31	45.34	29.99	26.54	34.84

Conclusions

The study demonstrates that incorporating expert-derived historical quantiles into a Bayesian framework substantially improves the estimation of short-duration rainfall extremes, particularly for low-probability events. Our analysis of the 1961–2009 series for Hurbanovo station demonstrates that record length substantially influences the estimated extreme rainfall quantiles, with at least 30 years of annual maxima needed for stable and reliable estimates.

The historical quantiles were incorporated using a Bayesian elicitation approach, allowing their informational value to contribute while explicitly accounting for uncertainty. By combining modern observations with expert knowledge from the period 1901–1965, the uncertainty in extreme quantile estimates is reduced, as reflected in narrower credible intervals. Additionally, the study highlights the value of temporal expansion and prior elicitation for anchoring extreme estimates, mitigating biases caused by anomalously mild periods in the instrumental record. The historical quantiles corresponding to AEP=0.05, 0.02, and 0.01 were higher for the period 1901–1965 than those derived from the period 1966–2009. This difference may be explained by more favorable conditions for the occurrence of more frequent and/or more intense convective precipitation during 1901–1965, which is also supported by the higher convective available potential energy (CAPE) derived from the ERA5 (Fig. 5).

Overall, the results confirm that eliciting priors from expert knowledge on historical quantiles narrows the uncertainty associated with low-probability exceedances. Expert information provides a robust supplement to relatively short instrumental datasets, enabling more reliable risk assessments for rare rainfall events. This approach suggests that future updates of national design rainfall atlases, such as the most recent atlas NKP 17/22 (Onderka and Pecho, 2023), could similarly benefit from incorporating expert-derived priors, thereby improving the reliability of extreme rainfall estimates in regions with limited observational data.

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