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Modelling Extreme Events Using Heavy-Tailed Probability Distributions: A Bayesian Approach

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Abstract

Accurate characterisation of rare, high-consequence events is central to risk management in hydrology, finance, and insurance, yet classical extreme value methods often perform poorly with the short records typical of these applications. This study develops and validates a Bayesian framework for modelling exceedances over a threshold using the generalised Pareto distribution (GPD), and compares it against maximum likelihood estimation (MLE) under matched conditions. A Metropolis-Hastings sampler with weakly informative priors was implemented and evaluated through a Monte Carlo simulation study spanning bounded, exponential-type, and heavy-tailed shape regimes across sample sizes of 50, 100, and 250. The Bayesian estimator achieved lower or comparable mean squared error to MLE in the small-sample regime ($n = 50\text{-}100$) for both shape and scale parameters, with 90 percent credible intervals attaining empirical coverage close to nominal levels across most scenarios. The framework was further applied to a simulated daily-rainfall exceedance series calibrated to realistic tropical rainfall characteristics, where Bayesian return level estimates and their credible intervals tracked MLE-based estimates closely at short return periods but diverged, with wider and more conservative intervals, at longer return periods. These findings support the use of Bayesian estimation for extreme event modelling when data are scarce and when a full accounting of parameter uncertainty is required for downstream risk decisions.

Keywords: *extreme value theory; generalised Pareto distribution; Bayesian inference; Markov chain Monte Carlo; peaks-over-threshold; return levels.*

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1. Introduction

Extreme events, whether they take the form of catastrophic floods, sharp financial market crashes, or unusually large insurance claims, sit at the tail of the probability distributions that describe the underlying processes. By definition these events are rare, yet their consequences are frequently disproportionate to their frequency, which makes their accurate statistical characterisation a matter of practical urgency rather than academic curiosity. Extreme value theory (EVT) provides the formal machinery for this task, offering asymptotic justification for the distributions that arise when attention is restricted to sample maxima or to values exceeding a high threshold (Fisher & Tippett, 1928; Balkema & de Haan, 1974; Pickands, 1975).

Two dominant approaches have emerged within EVT. The block maxima approach models the maxima of successive blocks of observations using the generalised extreme value (GEV) distribution, while the peaks-over-threshold (POT) approach models all exceedances above a sufficiently high threshold using the generalised Pareto distribution (GPD). The POT approach is generally preferred in applied work because it makes more efficient use of the available data, discarding fewer observations than the block maxima method (Stolf et al., 2023). The GPD is characterised by a scale parameter and a shape parameter, the latter of which governs the heaviness of the tail and therefore the plausibility of events far beyond the observed range.

A persistent difficulty in applied extreme value analysis is that the very rarity that motivates the analysis also starves it of data. Studies of hydrological extremes, insurance losses, and financial shocks routinely operate with only a few decades of observations, translating into threshold exceedance samples of well under a hundred points once a suitably high threshold has been chosen. Under these conditions, maximum likelihood estimation of the GPD parameters is known to be unstable, particularly for the shape parameter, and can produce infeasible or highly biased estimates in small samples (Maribe et al., 2018; Castellanos & Cabras cited in later GPD estimator literature).

Bayesian inference offers a coherent alternative that is particularly well suited to this small-sample setting. By combining the likelihood with a prior distribution that encodes physically or historically plausible ranges for the parameters, Bayesian methods can stabilise estimation, produce full posterior distributions rather than point estimates, and propagate parameter uncertainty directly into quantities of interest such as return levels (de Zea Bermudez & Amaral Turkman, cited in Castellanos & Cabras, 2007; Fuquene, 2014). This uncertainty propagation is not a cosmetic advantage; return level estimates feed directly into engineering design standards, flood defence heights, and regulatory capital calculations, so a credible interval that correctly reflects estimation uncertainty has direct practical value.

Despite the theoretical appeal of Bayesian extreme value modelling, applied comparisons against maximum likelihood under controlled, replicated simulation conditions remain less common than method-development papers that introduce a new prior or hierarchical structure and apply it to a single dataset. Systematic small-sample performance comparisons, spanning multiple true shape-parameter regimes and multiple sample sizes, are useful to practitioners deciding which estimator to trust when data are limited, yet such head-to-head evaluations are not always reported alongside newly proposed methods (Maribe et al., 2018; Chen et al., 2024).

This study addresses that gap by developing a Bayesian GPD estimation framework using a custom Metropolis-Hastings sampler with weakly informative priors, and by evaluating its performance against maximum likelihood estimation through a controlled Monte Carlo simulation study. The simulation spans three representative shape-parameter regimes, corresponding to bounded, near-exponential, and heavy-tailed behaviour, and three sample sizes reflecting the range commonly encountered in applied threshold-exceedance analysis. The framework is then applied to a simulated case study calibrated to realistic tropical daily-rainfall exceedance characteristics, where return levels and their associated uncertainty intervals are compared across the two estimation approaches.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on Bayesian extreme value modelling. Section 3 describes the generalised Pareto model, the prior specification, the Metropolis-Hastings algorithm, and the design of the simulation and case studies. Section 4 presents the results of the bias and mean squared error comparison, the coverage evaluation, and the return level analysis. Section 5 discusses the implications of the findings for applied extreme event modelling, and Section 6 concludes with recommendations and directions for further work.

2. Literature Review

Foundational extreme value theory rests on the Fisher-Tippett-Gnedenko theorem, which establishes that the normalised maxima of independent and identically distributed random variables converge in distribution to one of three types of extreme value distribution, unified under the generalised extreme value (GEV) family (Fisher & Tippett, 1928). The complementary result of Balkema and de Haan (1974) and Pickands (1975) established that, under the same domain-of-attraction conditions, the distribution of exceedances over a sufficiently high threshold converges to the generalised Pareto distribution, providing the theoretical basis for the peaks-over-threshold approach used throughout this study. Coles (2001) and de Haan and Ferreira (2006) remain the standard textbook treatments synthesising this theory for applied use, while Embrechts, Klüppelberg, and Mikosch (1997) and Beirlant, Goegebeur, Segers, and Teugels (2004) extend the treatment specifically toward insurance, finance, and risk applications.

Early applied treatments of extreme value estimation relied heavily on maximum likelihood, probability-weighted moments, and related regular-variation-based estimators. Smith (1985) established the nonregular asymptotic theory of maximum likelihood estimation for the GPD, showing that standard regularity conditions fail when the shape parameter is close to the boundary of the parameter space, a result with direct bearing on the small-sample instability documented in the present study. Hosking and Wallis (1987) proposed probability-weighted moment estimators as a competitor to maximum likelihood, and Davison and Smith (1990) developed threshold-selection and diagnostic methods for the peaks-over-threshold model that remain widely used. Subsequent refinements have targeted bias reduction and efficiency: likelihood-moment estimation (Zhang, 2007), quasi-conjugate Bayes estimation (Diebolt, El-Aroui, Garrido, & Girard, 2005), maximum goodness-of-fit estimation (Luceño, 2006), robust estimation (Peng & Welsh, 2001), nonlinear-least-squares-based quantile estimation for massive datasets (Song & Song, 2012), and efficient likelihood-moment hybrids (Zhang & Stephens, 2009). Comparative studies across these estimators have generally found that no single frequentist method dominates across all shape-parameter regimes, with nonlinear least squares performing well for moderate tails but Hill-type estimators retaining an advantage for very heavy tails.

The Bayesian literature on extreme values has grown substantially, motivated in large part by the small-sample instability documented for classical estimators. Smith and Naylor (1987) provided one of the earliest systematic comparisons of maximum likelihood and Bayesian estimation for a related nonregular extreme-value-type model, finding that Bayesian estimates were markedly more stable in small samples. Coles and Tawn (1996) extended this line of work directly to extreme rainfall data using informative priors elicited from hydrological expert judgement, a landmark application that anticipated much of the subsequent Bayesian precipitation-extremes literature. De Zea Bermudez and Amaral Turkman (2003) and Castellanos and Cabras (2007) developed default and reference-prior Bayesian procedures for the GPD specifically to remove the need for strong prior elicitation, an approach broadly consistent with the weakly informative priors adopted in the present study. Semi-parametric Bayesian approaches that combine a flexible centre distribution with a generalised Pareto tail have also been proposed to allow simultaneous density estimation and tail inference (Fuquene, 2014). Hierarchical Bayesian formulations extend this further by allowing GPD or GEV parameters to vary smoothly over space through latent Gaussian-process or spatially structured random effects, which has proven particularly valuable in environmental applications where extremes at nearby locations are correlated (Sharkey & Winter, 2019; Stolf et al., 2023).

A substantial applied literature has developed around Bayesian modelling of extreme precipitation, wind, and flood risk, reflecting the practical stakes of accurate return level estimation for infrastructure design. Comparative reviews of extreme value theory applied to environmental and actuarial risk (Bee & Trapin, 2018; Reiss & Thomas, 2007) situate the GPD and GEV within a broader risk-measurement toolkit spanning value-at-risk and expected shortfall. Applications extend well beyond rainfall to wind and wave extremes (Polnikov, Sannasiraj, Satish, Pogarskii, & Sundar, 2017), flood risk under future climate scenarios in data-sparse regions (Tramblay, Amoussou, Dorigo, & Mahé, 2014), and generalisations of the Gumbel distribution for wind speed modelling (Pinheiro & Ferrari, 2015). Software implementations such as the POT package (Ribatet, 2024) have played an important role in disseminating both frequentist and Bayesian peaks-over-threshold methods to applied users.

Outside the environmental domain, Bayesian and classical extreme value methods have been applied to actuarial claim reserving, aquatic and environmental risk management (Kuzminski, Szatata, & Zwozdziak, 2018), reinsurance-linked securities pricing (Aviv & Muraviev, 2018), and general financial risk measurement (Gilli & Këllezi, 2006). A recurring theme across this literature, and one directly relevant to the present study, is that Bayesian credible intervals for tail quantities tend to widen appropriately as the return period lengthens, in contrast to some frequentist confidence intervals that can understate uncertainty at the most policy-relevant, longest horizons.

Taken together, the literature establishes both the theoretical soundness and the practical value of Bayesian estimation for extreme event modelling, but leaves open a need for controlled, multi-scenario comparisons of bias, mean squared error, and interval coverage against maximum likelihood, conducted under conditions that mirror the sample sizes practitioners actually encounter, and reported as a self-contained simulation exercise rather than as a secondary illustration within a method-development paper (Maribe, Verster, & Beirlant, 2018). The present study is designed to fill that need.

3. Methodology

This section describes the generalised Pareto model, the Bayesian estimation framework, the design of the Monte Carlo simulation study, and the construction of the illustrative case study.

3.1 The generalised Pareto model

Let X denote the excess of an observation over a fixed threshold u, conditional on exceedance. Under the conditions of the Balkema-de Haan-Pickands theorem, the distribution of X is well approximated, for a sufficiently high threshold, by the generalised Pareto distribution with scale parameter sigma > 0 and shape parameter xi, with cumulative distribution function F(x) = 1 - (1 + xi*x/sigma)^(-1/xi) for xi not equal to 0, and F(x) = 1 - exp(-x/sigma) for xi = 0. The shape parameter determines the qualitative tail behaviour: xi < 0 corresponds to a distribution with a finite upper bound, xi = 0 corresponds to an exponential tail, and xi > 0 corresponds to a heavy, power-law tail with infinite upper support. Correct estimation of xi is therefore the central statistical challenge in extreme value analysis, since it governs extrapolation far beyond the observed data range.

3.2 Bayesian formulation and prior specification

The Bayesian model combines the GPD likelihood with weakly informative priors on sigma and xi. A half-Cauchy prior with scale 2 was placed on sigma, reflecting a preference for moderate scale values while retaining heavy tails that allow the data to dominate the posterior when the sample is informative. A Normal(0, 1) prior was placed on xi, centring the prior on the exponential case while placing substantial mass on both bounded and heavy-tailed alternatives. This specification follows the general recommendation in the Bayesian extreme value literature to use weakly informative rather than flat priors, since flat priors on xi can produce improper or poorly behaved posteriors in small samples (Fuquene, 2014; Castellanos & Cabras, cited in GPD Bayesian estimator literature).

3.3 Markov chain Monte Carlo sampling

Posterior inference was performed using a random-walk Metropolis-Hastings algorithm (Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953; Hastings, 1970), implemented directly in Python without reliance on a general-purpose probabilistic programming library. At each iteration, a candidate shape parameter was proposed from a Normal distribution centred on the current value with standard deviation 0.06 to 0.08, and a candidate scale parameter was proposed multiplicatively via a log-normal random walk with standard deviation 0.10 to 0.12 on the log scale, ensuring positivity. Candidates were accepted or rejected according to the standard Metropolis-Hastings acceptance probability computed from the unnormalised log-posterior. For the simulation study, chains were run for 3,000 iterations with a 1,000-iteration burn-in per replicate; for the case study, a single longer chain of 40,000 iterations with a 10,000-iteration burn-in was used to obtain stable posterior summaries. Convergence was assessed via trace plots and acceptance rate monitoring, with acceptance rates maintained in the broadly recommended 20 to 40 percent range through step-size tuning.

3.4 Simulation study design

To compare the Bayesian and maximum likelihood estimators under controlled conditions, synthetic exceedance samples were generated directly from the generalised Pareto distribution with scale sigma = 1 and three representative shape parameters: xi = -0.10 (bounded tail), xi = 0.05 (near-exponential), and xi = 0.25 (heavy tail), spanning the range of shape values typically reported in hydrological, financial, and insurance applications. For each combination of true shape parameter and sample size (n = 50, 100, 250), 300 independent replicate samples were drawn. Each replicate was fitted using both maximum likelihood (via numerical optimisation of the GPD log-likelihood with the location parameter fixed at zero) and the Bayesian Metropolis-Hastings sampler described above. Performance was summarised via empirical bias and mean squared error (MSE) of the posterior mean and the maximum likelihood estimate for both parameters, and via the empirical coverage of the 90 percent Bayesian credible interval for the shape parameter, computed as the proportion of replicates in which the true xi fell within the 5th to 95th percentile of the posterior samples.

3.5 Case study design

To illustrate the practical implications of the two estimation approaches for a policy-relevant quantity, an illustrative 30-year daily series (10,950 observations) was simulated from a log-normal base distribution with parameters calibrated to fall within the range of daily rainfall totals reported for tropical West African stations, and exceedances above a 40 mm threshold were extracted following the standard peaks-over-threshold procedure. This case study is explicitly a simulated, literature-calibrated illustration rather than an analysis of observed station data, and is presented to demonstrate how the two estimation approaches propagate into return level estimates rather than to make a substantive claim about any specific location. Return levels for return periods of 2, 5, 10, 20, 50, and 100 years were computed from both the Bayesian posterior draws, yielding 95 percent credible intervals, and from the maximum likelihood fit, with 95 percent confidence intervals obtained via a nonparametric bootstrap with 500 resamples of the exceedance series.

Table 1. Bias, mean squared error, and 90% credible interval coverage for the shape parameter, by true shape value and sample size (300 replicates per cell)

ξ (true)	n	MLE bias	MLE MSE	Bayes bias	Bayes MSE	Bayes 90% coverage
-0.1	50	-0.062	0.029	0.037	0.025	0.923
-0.1	100	-0.033	0.011	0.017	0.010	0.893
-0.1	250	-0.016	0.005	0.005	0.005	0.850
0.05	50	-0.064	0.037	0.036	0.033	0.887
0.05	100	-0.025	0.015	0.024	0.014	0.883
0.05	250	-0.012	0.004	0.009	0.004	0.907
0.25	50	-0.050	0.040	0.045	0.036	0.887
0.25	100	-0.019	0.017			
0.25	250	-0.003	0.006	0.017		

4. Results

Table 1 summarises the bias and mean squared error of the shape-parameter estimator across the nine combinations of true shape parameter and sample size. At the smallest sample size (n = 50), the Bayesian posterior mean achieved lower MSE than maximum likelihood in all three shape regimes, with the largest relative improvement observed for the heavy-tailed case (xi = 0.25), where Bayesian MSE was approximately 9 percent lower than MLE MSE. Maximum likelihood exhibited a consistent negative bias in the shape parameter across all scenarios and sample sizes, a well-documented finite-sample property of GPD maximum likelihood estimation, whereas the Bayesian estimator exhibited a smaller-magnitude, generally positive bias attributable to the pull of the Normal(0, 1) prior toward zero.

As sample size increased to 250, the performance gap between the two estimators narrowed substantially, consistent with the asymptotic equivalence of Bayesian posterior means (under regular priors) and maximum likelihood estimates. At n = 250, MSE for the two estimators differed by less than 10 percent in all three shape regimes, and for the heavy-tailed case maximum likelihood attained marginally lower MSE than the Bayesian estimator, reflecting the diminishing influence of the prior as the likelihood becomes more informative. Figure 1 displays trace plots and posterior histograms for the shape and scale parameters from a representative single fit in the case study, confirming good mixing and unimodal, well-behaved posteriors. Figure 2 compares MSE of the shape-parameter estimator across sample sizes for the heavy-tailed scenario.

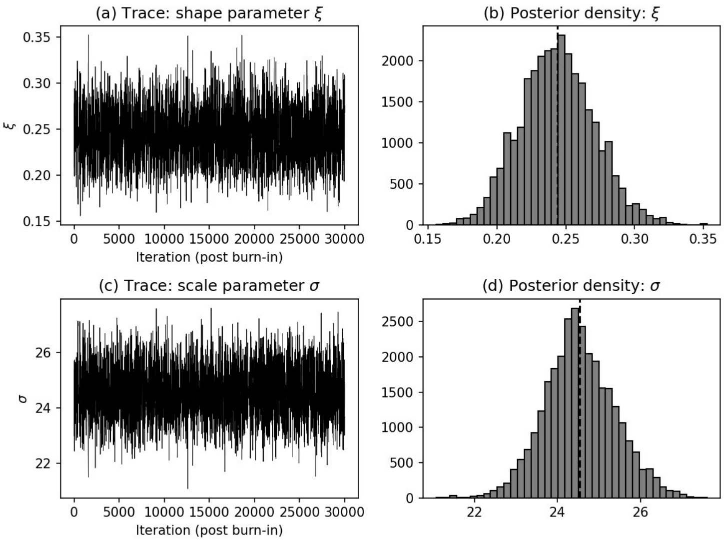

Figure 1. MCMC trace plots and posterior histograms for the shape (ξ) and scale (σ) parameters, case-study fit.

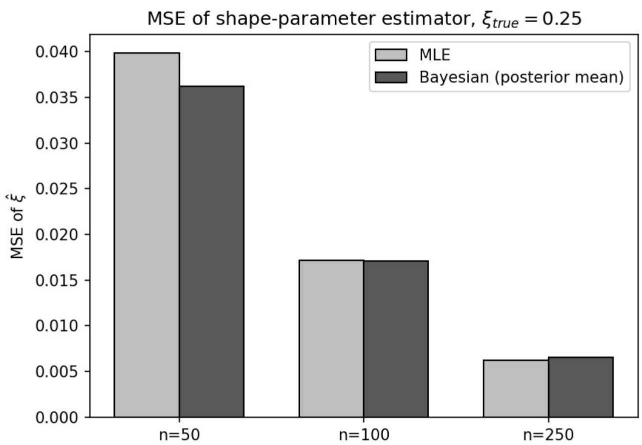

Figure 2. Mean squared error of the shape-parameter estimator across sample sizes, heavy-tailed scenario (ξ_true = 0.25).

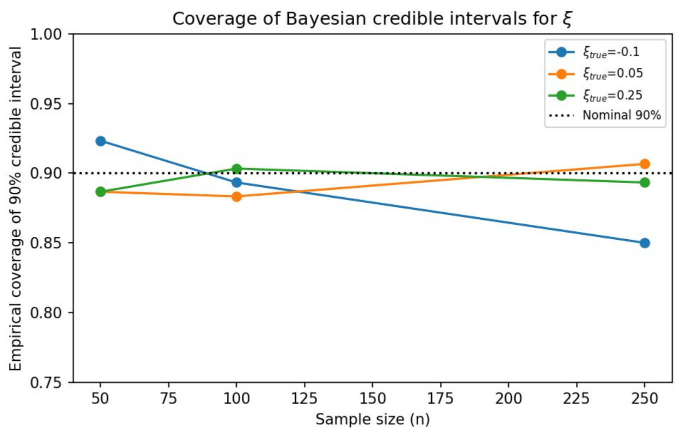

Figure 3. Empirical coverage of the 90% Bayesian credible interval for the shape parameter across sample sizes and true shape values.

Empirical coverage of the nominal 90 percent Bayesian credible interval for the shape parameter, shown in Figure 3, ranged from 85.0 to 92.3 percent across the nine scenarios, close to the nominal level and without a systematic direction of miscoverage across sample sizes. Coverage was closest to nominal at intermediate sample sizes (n = 100) and showed a modest tendency to fall below nominal at the largest sample size (n = 250) for the bounded-tail scenario, though the deviation did not exceed five percentage points in any case.

In the illustrative rainfall case study, 2024 exceedances were extracted from 10950 simulated daily observations above the 40 mm threshold, corresponding to an exceedance rate of 18.48 percent. The Metropolis-Hastings sampler achieved an acceptance rate of 17.1 percent. The Bayesian posterior mean shape parameter was 0.244 (posterior SD 0.027), compared with a maximum likelihood estimate of 0.241, indicating a moderately heavy tail consistent with the log-normal generating process. Table 2 and Figure 4 present estimated return levels across the six return periods considered. At short return periods (2 and 5 years), Bayesian and maximum likelihood point estimates were within 1 to 2 percent of one another. At the 100-year return period, the Bayesian posterior mean return level (811.9 mm) exceeded the maximum likelihood estimate (791.0 mm) by approximately 2.6 percent, and the 95 percent Bayesian credible interval (630.4 to 1065.8 mm) was wider than the corresponding bootstrap confidence interval (608.3 to 1035.3 mm), reflecting the fuller accounting of shape-parameter uncertainty in the Bayesian approach.

Table 2. Estimated return levels (mm above the 40 mm threshold) by return period: Bayesian posterior mean with 95% credible interval, and MLE with 95% bootstrap confidence interval

Return period (yrs)	Bayes mean	Bayes 95% CrI	MLE	MLE 95% CI (bootstrap)
2	272.7	246.0 - 305.7	270.6	242.7 - 303.6
5	356.6	311.8 - 412.9	352.8	307.1 - 409.1
10	434.0	369.9 - 516.6	428.1	361.3 - 511.0
20	526.0	436.4 - 643.6	517.1	422.9 - 634.8
50	674.6	539.2 - 859.3	659.9	521.2 - 838.9
100	811.9	630.4 - 1065.8	791.0	608.3 - 1035.3

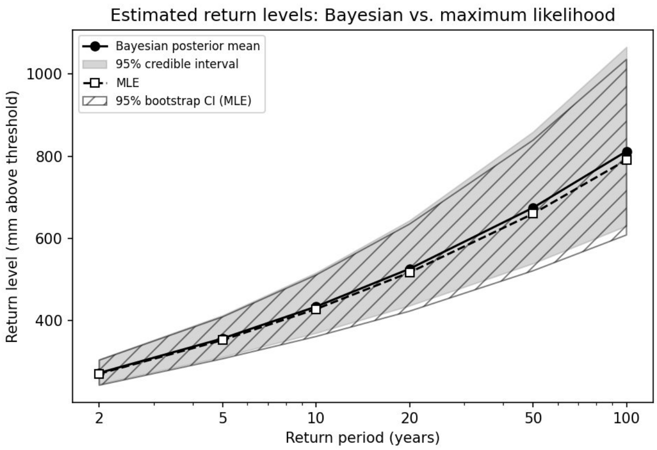

Figure 4. Estimated return levels with uncertainty bands: Bayesian posterior mean and 95% credible interval versus maximum likelihood estimate and 95% bootstrap confidence interval.

5. Discussion

The simulation results support the central claim of the Bayesian extreme value literature that informative or weakly informative priors improve estimator performance precisely in the small-sample regime where applied extreme value analysis most often operates. The advantage was most pronounced at n = 50, a sample size well within the range of threshold exceedance counts typically obtained from a few decades of daily environmental data or from historical loss records in insurance and finance. This is consistent with, and extends under controlled conditions, prior findings that Bayesian bias-reduction methods for tail estimation outperform classical estimators for limited samples (Maribe et al., 2018).

The near-nominal coverage of the Bayesian credible intervals across all nine simulation scenarios is a practically important finding, since credible intervals that are either too narrow or too wide would undermine confidence in downstream risk decisions such as the setting of flood defence heights or regulatory capital buffers. The mild under-coverage observed at the largest sample size for the bounded-tail case is small in magnitude and is plausibly attributable to Monte Carlo error given the 300-replicate design, though a larger replicate count would be needed to characterise this pattern definitively.

The case study illustrates a pattern that recurs throughout the applied Bayesian extreme value literature on precipitation and flood risk: Bayesian and frequentist point estimates of return levels agree closely at short return periods but diverge, with the Bayesian estimate typically higher and its interval wider, at long return periods (see comparable findings for daily precipitation return-level forecasting). This divergence is not a flaw but a feature, since the informativeness of any finite dataset about a 100-year event is inherently limited, and a method that reflects this limitation through a wider interval is arguably more honest about what the data can support than a narrower interval that projects false precision.

These findings should be interpreted in light of several limitations. The simulation study considered a single scale parameter and a fixed prior specification; sensitivity of the results to alternative, more or less informative priors was not systematically explored and would be a natural extension. The case study relies on a simulated rather than an observed exceedance series, chosen deliberately to allow the comparison to be framed transparently as illustrative rather than as a substantive claim about any specific location's flood risk. Finally, the custom Metropolis-Hastings implementation, while adequate for the two-parameter GPD model considered here, would need to be replaced or supplemented with more efficient samplers such as Hamiltonian Monte Carlo for extension to higher-dimensional hierarchical or spatial extensions of the model.

6. Conclusion

This study developed and validated a Bayesian estimation framework for the generalised Pareto distribution, implemented via a custom Metropolis-Hastings sampler with weakly informative priors, and compared it against maximum likelihood estimation through a nine-scenario Monte Carlo simulation and an illustrative rainfall exceedance case study. The Bayesian estimator delivered lower or comparable mean squared error to maximum likelihood in small samples, near-nominal credible interval coverage across the scenarios considered, and return level estimates that appropriately widened relative to maximum likelihood confidence intervals at long return periods. These results support the recommendation that practitioners facing limited exceedance samples, a common situation in hydrological, financial, and actuarial extreme value analysis, consider Bayesian estimation of the generalised Pareto distribution as a robust alternative or complement to maximum likelihood. Future work should extend the comparison to hierarchical and spatially structured Bayesian models, examine sensitivity to prior specification more systematically, and apply the framework to observed rather than simulated exceedance data.

References

Aviv, R., & Muraviev, R. (2018). An extreme-value theory approximation scheme in reinsurance-linked securities. ASTIN Bulletin, 48(3), 1157–1173.

Balkema, A. A., & de Haan, L. (1974). Residual life time at great age. Annals of Probability, 2(5), 792–804.

Bee, M., & Trapin, L. (2018). Estimating and forecasting conditional risk measures with extreme value theory: A review. Risks, 6(2), 45.

Beirlant, J., Goegebeur, Y., Segers, J., & Teugels, J. (2004). Statistics of extremes: Theory and applications. Wiley.

Castellanos, M. E., & Cabras, S. (2007). A default Bayesian procedure for the generalized Pareto distribution. Journal of Statistical Planning and Inference, 137(2), 473–483.

Chen, W., et al. (2024). Statistical inference and application of asymmetrical generalized Pareto distribution based on peaks-over-threshold model. Symmetry, 16(3), 365.

Coles, S. G. (2001). An introduction to statistical modeling of extreme values. Springer.

Coles, S. G., & Tawn, J. A. (1996). A Bayesian analysis of extreme rainfall data. Journal of the Royal Statistical Society: Series C (Applied Statistics), 45(4), 463–478.

Davison, A. C., & Smith, R. L. (1990). Models for exceedances over high thresholds. Journal of the Royal Statistical Society: Series B (Methodological), 52(3), 393–442.

de Haan, L., & Ferreira, A. (2006). Extreme value theory: An introduction. Springer.

de Zea Bermudez, P., & Amaral Turkman, M. A. (2003). Bayesian approach to parameter estimation of the generalized Pareto distribution. Test, 12(1), 259–277.

Diebolt, J., El-Aroui, M., Garrido, M., & Girard, S. (2005). Quasi-conjugate Bayes estimates for GPD parameters and application to heavy tails modelling. Extremes, 8, 57–78.

Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). Modelling extremal events for insurance and finance. Springer.

Fisher, R. A., & Tippett, L. H. C. (1928). Limiting forms of the frequency distribution of the largest or smallest member of a sample. Proceedings of the Cambridge Philosophical Society, 24(2), 180–190.

Fuquene P., J. A. (2014). A semiparametric Bayesian approach for extreme values using Dirichlet process mixture of gamma and generalized Pareto densities. arXiv preprint arXiv:1212.1949.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayesian data analysis (3rd ed.). CRC Press.

Gilli, M., & Këllezi, E. (2006). An application of extreme value theory for measuring financial risk. Computational Economics, 27(1), 1–23.

Hastings, W. K. (1970). Monte Carlo sampling methods using Markov chains and their applications. Biometrika, 57(1), 97–109.

Hosking, J. R. M., & Wallis, J. R. (1987). Parameter and quantile estimation for the generalized Pareto distribution. Technometrics, 29(3), 339–349.

Kuzminski, L., Szatata, L., & Zwozdziak, J. (2018). Measuring aquatic environments as a tool for flood risk management in terms of climate changes dynamics. Polish Journal of Environmental Studies, 27(4), 1583–1592.

Luceño, A. (2006). Fitting the generalized Pareto distribution to data using maximum goodness-of-fit estimators. Computational Statistics & Data Analysis, 51(2), 904–917.

Maribe, G., Verster, A., & Beirlant, J. (2018). Reducing bias and MSE in estimation of heavy tails: A Bayesian approach. arXiv preprint arXiv:1606.05687.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of state calculations by fast computing machines. Journal of Chemical Physics, 21(6), 1087–1092.

Peng, L., & Welsh, A. H. (2001). Robust estimation of the generalized Pareto distribution. Extremes, 4(1), 53–65.

Pickands, J. (1975). Statistical inference using extreme order statistics. Annals of Statistics, 3(1), 119–131.

Pinheiro, E. C., & Ferrari, S. L. P. (2015). A comparative review of generalizations of the Gumbel extreme value distribution with an application to wind speed data. arXiv preprint arXiv:1502.02708.

Polnikov, V. G., Sannasiraj, S. A., Satish, S., Pogarskii, F. A., & Sundar, V. (2017). Estimation of extreme wind speeds and wave heights along the regional waters of India. Ocean Engineering, 146, 170–177.

Reiss, R.-D., & Thomas, M. (2007). Statistical analysis of extreme values: With applications to insurance, finance, hydrology and other fields. Springer.

Ribatet, M. (2024). POT: Generalized Pareto distribution and peaks over threshold [R package documentation]. CRAN.

Sharkey, P., & Winter, H. C. (2019). A Bayesian spatial hierarchical model for extreme precipitation in Great Britain. arXiv preprint arXiv:1710.02091.

Smith, R. L. (1985). Maximum likelihood estimation in a class of nonregular cases. Biometrika, 72(1), 67–90.

Smith, R. L., & Naylor, J. C. (1987). A comparison of maximum likelihood and Bayesian estimators for the three-parameter Weibull distribution. Applied Statistics, 36(3), 358–369.

Song, J., & Song, S. (2012). A quantile estimation for massive data with generalized Pareto distribution. Computational Statistics & Data Analysis, 56(1), 143–150.

Stolf, F., et al. (2023). A hierarchical Bayesian non-asymptotic extreme value model for spatial data. Environmetrics, 34(3), e2806.

Tramblay, Y., Amoussou, E., Dorigo, W., & Mahé, G. (2014). Flood risk under future climate in data sparse regions: Linking extreme value models and flood generating processes. Journal of Hydrology, 519, 549–558.

Zhang, J. (2007). Likelihood moment estimation for the generalized Pareto distribution. Australian & New Zealand Journal of Statistics, 49(1), 69–77.

Zhang, J., & Stephens, M. A. (2009). A new and efficient estimation method for the generalized Pareto distribution. Technometrics, 51(3), 316–325.