



Residual error modelling for process-based flood frequency analysis

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Abstract. Flood frequency analysis (FFA) is essential for flood risk management and infrastructure design, yet estimates of flood quantiles remain strongly influenced by the length and representativeness of available streamflow record. We introduce UQ-flood, a process-based flood-frequency framework that integrates a stochastic weather generator, a process-based hydrologic model, and a residual error model developed at the annual-maximum scale. The framework explicitly addresses the presence of errors in simulated annual flood peaks generated by models calibrated to continuous streamflow data. We apply UQ-flood to three Canadian watersheds with contrasting hydroclimatic conditions using 30 years of meteorological and streamflow observations. Long-record empirical annual-maximum estimates provide the primary benchmark, while Bayesian Generalized Extreme Value estimates based on short and long records provide secondary statistical benchmarks for the central flood-quantile estimates. Across the three watersheds, the central UQ-flood estimates remained within the confidence intervals for the long-record discharge quantiles, although their relative proximity to the empirical estimates varied by watershed and return period. Process-based simulations without residual-error correction systematically underestimated flood magnitudes, whereas applying the residual error model shifted the estimated flood-frequency curves toward the long-record observational benchmarks. The framework also propagates residual predictive variability directly at the annual-maximum scale. These results demonstrate that annual-maximum residual error modelling can correct for systematic discrepancies in process-based flood estimates and support central flood-quantile estimation even at sites with short data records.

1 Introduction

Floods are among the most prevalent natural disasters, with both their intensity and frequency increasing due to global change (Milly et al., 2002). In this context, flood frequency analysis (FFA) plays a fundamental role in engineering hydrology, as it is essential for accurately estimating flood risks. These estimations are critical for designing flood protection infrastructure, planning land use, ensuring dam and industrial safety, conducting risk assessments, and making informed water resources management decisions. Industry-standard, at-site FFA typically involves fitting a statistical distribution to a sample of observed flood data, often based on annual maximum flows or peaks over threshold (POT). These distribution models estimate the probability of exceedance for extreme flood peaks and are used to extrapolate high flood quantiles beyond observed data, often following regulatory guidelines (Hamed and Ramachandra Rao, 2019).

In this study, process-based flood frequency analysis refers to the generation of synthetic meteorological sequences, their transformation into streamflow through a hydrologic model, and the subsequent estimation of flood quantiles from the resulting annual-maximum series. Uncertainty quantification is an established component of statistical flood-frequency analysis, and conventional guidance includes procedures for reporting confidence limits for estimated flood quantiles (England et al., 2018). These intervals commonly characterize sampling and parameter uncertainty conditional on the selected probability model, although statistical frameworks can also incorporate distributional model uncertainty explicitly (Liang et al., 2012; Merz and Thielen, 2005). In process-based flood frequency analysis, additional uncertainty arises from the broader hydrometeorological modelling chain, including meteorological inputs and weather-generator parameters, hydrologic-model structure and parameters, antecedent

conditions, and errors in simulated flood peaks (Arnaud et al., 2017; Cameron et al., 2000; Newman et al., 2021). These components are not automatically represented by conventional at-site statistical confidence intervals and therefore require explicit evaluation and propagation within the process-based simulation framework.

Statistical FFA based on limited streamflow records, for example fewer than 30 years of annual maximum flows, can yield highly uncertain and often impractical estimates for rare events. In such cases, uncertainty intervals may be statistically defensible but so wide that they provide limited actionable guidance for infrastructure design, floodplain mapping, or emergency planning. This limitation highlights a key gap: the need for accessible and reliable uncertainty quantification approaches that remain useful under data-scarce conditions (Pappenberger and Beven, 2006).

Several strategies have been developed to reduce the limitations imposed by short flood records. A first option is to extend the flood record in time by incorporating historical information, documentary evidence, or paleoflood indicators (Benito et al., 2004). These approaches can improve the estimation of rare flood quantiles by adding information about events that occurred before systematic gauging began. However, they also require careful treatment of additional uncertainty sources, including event dating, magnitude reconstruction, threshold interpretation, and differences between historical, paleoflood, and instrumental data quality. Thus, while historical and paleoflood information can increase the effective sample size, it can also introduce new epistemic uncertainties that must be explicitly characterised.

A second option is to borrow information across space through regional flood frequency analysis, where data from hydrologically similar catchments are pooled to increase the effective flood sample (Cunnane, 1988). Regional approaches can reduce sampling uncertainty relative to single-site analysis, particularly in basins with short records. However, their reliability depends on the assumption that the selected catchments form a homogeneous region. Defining such regions is partly subjective and depends on choices regarding similarity criteria, catchment descriptors, regional boundaries, and pooling rules. As a result, different regionalization decisions can lead to different pooled samples and, consequently, different flood quantile estimates.

A third option is to generate larger flood samples using process-based continuous simulation, in which stochastic weather generators, stochastic storm transposition, or other meteorological resampling approaches are coupled with hydrologic models to produce long synthetic streamflow records (Eagleson, 1972; Franchini et al., 1996). This approach is attractive because it can represent physical controls on flood generation, including interactions among rainfall, snowpack, soil moisture, antecedent storage, and runoff production, while reducing sampling uncertainty through large synthetic samples. Previous studies have established the conceptual and practical basis of process-based FFA across a

range of hydrologic settings and modelling configurations (Arnaud and Lavabre, 2002; Blazkova and Beven, 2009; Haberlandt and Radtke, 2014; Perez et al., 2019; Sivapalan et al., 2005; Yu et al., 2019). More recent developments have expanded this approach by using stochastic storm transposition to preserve the spatial and temporal characteristics of observed storms. Comparisons with conventional design-storm methods show that simplifying the spatiotemporal variability of rainfall can misrepresent flood hazard and risk, with important implications for infrastructure design, floodplain mapping, land-use planning, and disaster-risk management (Baer et al., 2026). Process-based FFA has also advanced using spatially distributed and more physically detailed hydrologic models. For example, coupling stochastic storm transposition with an integrated surface–subsurface hydrologic model extends the analysis beyond peak-flow frequency to include spatially distributed flood extent and population exposure (Perez et al., 2024). Together, these developments demonstrate how process-based FFA can move beyond simplified design-event assumptions and more explicitly represent the interacting meteorological, surface, and subsurface processes controlling flood magnitude and spatial extent. Nevertheless, the resulting estimates remain conditional on the adequacy of the meteorological sampling method, hydrologic-model structure, parameterization, and representation of the dominant flood-generating processes.

Model-based approaches are particularly well-suited for this task because they capture complex interactions among flood drivers – such as rainfall, snowpack, and soil moisture – and their influence on runoff production (Sivapalan and Samuel, 2009). In contrast to design storm methods, model-based FFA avoids the assumption of equal return periods for rainfall and discharge. It also enables the integration of land use change (e.g., urbanization), management interventions, and future climate scenarios (Lamb et al., 2016). Another key advantage of this approach is its ability to generate large synthetic samples, which reduces sampling uncertainty – a common limitation in statistical methods relying on short observational records. Common methods to generate large prediction samples for this framework include stochastic weather generators using multivariate non-Gaussian time series (e.g., Yu et al., 2023), stochastic storm transpositions (Andersen et al., 2024; Wright et al., 2020), and reforecast ensemble pooling (Brunner and Slater, 2022). However, continuous simulation does not automatically solve the uncertainty problem in FFA. A key limitation is that hydrologic models are commonly calibrated to reproduce daily streamflow dynamics or general hydrograph behaviour, whereas FFA depends on accurately representing annual maximum flows. This creates a mismatch between the calibration target and the design variable of interest. A model that performs well for daily streamflow may still exhibit systematic bias or inadequate variability in simulated flood peaks (Cameron et al., 2000; Brunner et al., 2021; Grimaldi et al., 2019; Spellman et al., 2018). If this model error is ignored, continuous simulation can pro-

duce biased flood frequency estimates, even when very long synthetic streamflow records are generated.

Several methodological frameworks have been proposed to quantify the uncertainty of flood frequency estimates, yet none have achieved widespread adoption in practice. One class of approaches combines continuous hydrologic model simulation with stochastic rainfall generation and rainfall–runoff modelling, often using methods like Generalized Likelihood Uncertainty Estimation (GLUE) to quantify uncertainty (Cameron et al., 2000). While GLUE is useful for exploring parameter and model structure uncertainty, it has been criticized for relying on subjective likelihood measures and for its tendency to overestimate uncertainty (Stedinger et al., 2008). Formal Bayesian inference methods offer a more robust probabilistic treatment of uncertainty, but they are often computationally demanding and require careful specification of prior distributions, limiting their accessibility for routine applications (Costa and Fernandes, 2017). Other approaches, including resampling methods, hierarchical Monte Carlo frameworks, variance decomposition, and ensemble pooling, have also been used to reduce or attribute uncertainty in flood estimates (Apel et al., 2004; Arnaud et al., 2017; Bomers et al., 2019; Burn, 2003; Mirzaei et al., 2015; Newman et al., 2021; Brunner and Slater, 2022). Despite this diversity of methods, many remain constrained by subjectivity, computational complexity, high data requirements, or limited treatment of hydrologic model error at the flood-peak scale. A more accessible, process-consistent framework for uncertainty quantification in FFA – particularly one that performs well under limited data availability – therefore remains a pressing need.

Given these limitations, process-based FFA requires an explicit treatment of hydrologic model error at the scale most relevant for design floods: the annual maximum flow. A key limitation of model-based flood estimation frameworks is the frequent neglect of model error and uncertainty in hydrologic predictions. To address this, we apply the Residual Error Model (REM) approach – a strategy designed to quantify and propagate residual uncertainty by embedding error model samples into calibrated deterministic simulations (Vogel, 2017). REM transforms deterministic outputs from process-based hydrological models into streamflow ensembles, offering a robust means of uncertainty quantification that is particularly valuable for hydrologic risk management. The REM framework consists of two key components:

1. A deterministic component, which represents changes in meteorological forcings, land use, and their non-linear interactions.
2. A stochastic component, which accounts for hydrologic uncertainty not captured by the deterministic model alone (Shabestanipour et al., 2023).

This dual structure enables REM to estimate predictive uncertainty – integrating data, parametric, and structural un-

certainties – by comparing model simulations with observed streamflow records (Montanari and Koutsoyiannis, 2012). Various error modelling approaches have been proposed to represent this uncertainty (Jiang et al., 2019; Koutsoyiannis and Montanari, 2022; Li et al., 2016; McInerney et al., 2017, 2020; Shabestanipour et al., 2023; Todini, 2008).

In this study, we apply a REM that is additive in the transformed space, using the Box–Cox transformation, Gaussian innovations, and a flow-dependent error mean – following the formulation in Hunter et al. (2021). This error model is particularly attractive due to its ability to consolidate multiple sources of uncertainty into a single error term, enabling transparent, efficient, and straightforward generation of streamflow predictive distributions (Evin et al., 2014; Romero-Cuellar et al., 2024).

Here, we present UQ-flood, an uncertainty quantification framework for process-based flood frequency analysis that integrates a process-based hydrologic model, a stochastic weather generator, and a residual error model developed at the annual maxima scale. The framework is designed to generate large synthetic flood samples while correcting systematic biases and propagating residual uncertainty in simulated flood peaks. By modelling the relationship between observed and simulated annual maximum flows directly, UQ-flood addresses the mismatch between daily streamflow calibration and flood-quantile estimation. This allows uncertainty from hydrologic simulation to be propagated into flood frequency curves and associated quantile estimates. The novelty of this study lies not in process-based continuous simulation alone, but in applying a residual error model directly at the annual-maximum scale and embedding it within a stochastic simulation framework for at-site FFA. This differs from daily-flow post-processing and from parameter-uncertainty approaches because it targets the design variable itself: annual maximum discharge.

Unlike traditional statistical FFA methods that rely solely on observed flood samples and assumed parametric distributions, UQ-flood is informed by hydrologic process representation and by the full information contained in the available meteorological and discharge records. To our knowledge, this is the first study to apply the REM approach within the context of at-site FFA for uncertainty quantification. In contrast to conventional approaches that can produce very wide uncertainty intervals under short-record conditions, UQ-flood offers a process-consistent and practical alternative for data-scarce environments.

2 Study Watersheds and Data

To evaluate the proposed UQ-flood framework for at-site application across diverse hydrologic conditions, we selected three Canadian case study watersheds based on two main criteria: (1) the availability of long daily streamflow records – each with more than 80 years of data – to enable valida-

tion of flood frequency estimates, and (2) minimal anthropogenic regulation, as the hydrologic models used in this study do not simulate human interventions such as reservoir operations or flow diversions. In addition to these criteria, we deliberately chose three watersheds that represent contrasting physiographic and climatic regions. The Lahave River in Nova Scotia was selected to represent coastal catchments influenced by maritime climate conditions; the Moyie River in British Columbia serves as a representative mountain watershed with a snowmelt-dominated regime; and the Black River in Ontario captures characteristics of the Great Lakes region, including wetland and lake-dominated hydrology.

2.1 Black River Watershed

The Black River near Washago is in central Ontario, Canada, and drains a watershed of approximately 1506 km² upstream of the Water Survey of Canada gauge 02EC002, which has over 100 years of streamflow records. The watershed is characterised by a humid continental climate, with cold, snowy winters and warm, humid summers. The climate is strongly influenced by the Great Lakes, which moderate seasonal temperatures and enhance precipitation (Whitfield and Cannon, 2000). Hydrologically, the Black River is classified as a mixed-regime system, with a dominant nival (snowmelt) component; the nival fraction is approximately 0.7 (Burn and Whitfield, 2023). The primary flood-generating mechanisms are spring snowmelt and rain-on-snow events, which have historically produced the highest flows (Buttle et al., 2016). The watershed contains a high proportion of wetlands, which play a key role in sustaining groundwater recharge, and maintaining baseflow during dry periods.

2.2 Moyie River Watershed

The Moyie River is in southeastern British Columbia within the South BC Mountains region and drains an area of approximately 1480 km² upstream of the Water Survey of Canada gauge 08NH006, which provides a 90-year observational record. The watershed lies within a complex mountainous terrain characterised by steep slopes, dense forest cover, and variable elevations. The climate is strongly influenced by elevation and orographic effects, resulting in a continental to subalpine climate with distinct seasonal patterns. Winters are cold with substantial snowfall, while summers are warm and relatively dry (Whitfield and Cannon, 2000). The hydrologic regime is snowmelt-dominated, with peak flows typically occurring in late spring to early summer (May–June). Rain-on-snow events in late winter or early spring also contribute to flood risk, particularly when rapid warming occurs on an established snowpack (Buttle et al., 2016).

2.3 Lahave River Watershed

The Lahave River at West Northfield is in Nova Scotia and drains an area of approximately 1250 km² upstream of the

Water Survey of Canada gauge 01EF001, providing 108 years of continuous daily flow records. The watershed is situated within a coastal, lowland physiographic region and is characterised by rolling hills, mixed forest, and numerous lakes and wetlands. The region experiences a humid maritime climate, with relatively mild winters, cool summers, and high precipitation distributed evenly throughout the year. This climate is strongly influenced by proximity to the Atlantic Ocean, which moderates seasonal temperature fluctuations and contributes to frequent rainfall. The area is also regularly affected by storms, including tropical cyclones and hurricanes, due to its exposure to Atlantic storm tracks (Whitfield and Cannon, 2000). Hydrologically, the Lahave River exhibits a rainfall-dominated regime, with flood events occurring year-round, but most frequently in the fall and winter when intense rainfall coincides with saturated soil conditions. Rain-on-snow events may also contribute to elevated flows during transitional seasons; however, snow accumulation is generally lower than in inland or higher-elevation watersheds (Buttle et al., 2016). Figure 1 shows the location of three study watersheds.

3 Methodology

The UQ-flood framework proposed in this study integrates three key components: a process-based hydrological model, a residual error model (REM), and a stochastic weather generator (SWG). These components are used in conjunction to quantify the model uncertainty in flood estimates. The framework consists of two main phases: (1) model setup and parameter estimation; and (2) long-term continuous simulation, as schematically illustrated in Fig. 2. The key steps are outlined as follows:

– Phase 1: Model Setup and Parameter Estimation

1. Build a process-based hydrological model. The first step involves developing a hydrological model capable of simulating river discharge based on the physical processes governing the watershed. This model serves as the backbone for simulating runoff and streamflow under given climatic conditions.
2. Develop a residual error model (REM) based on annual maxima. The residual error model is developed to characterise and quantify uncertainties in hydrological predictions, specifically for extreme events. It is constructed using the annual maximum flow series, by analysing the differences between observed and simulated annual maxima. This approach captures the statistical properties of model errors – including their magnitude and variability at the scale most relevant for flood frequency analysis.
3. Set up a stochastic weather generator (SWG). The SWG is configured to generate synthetic weather

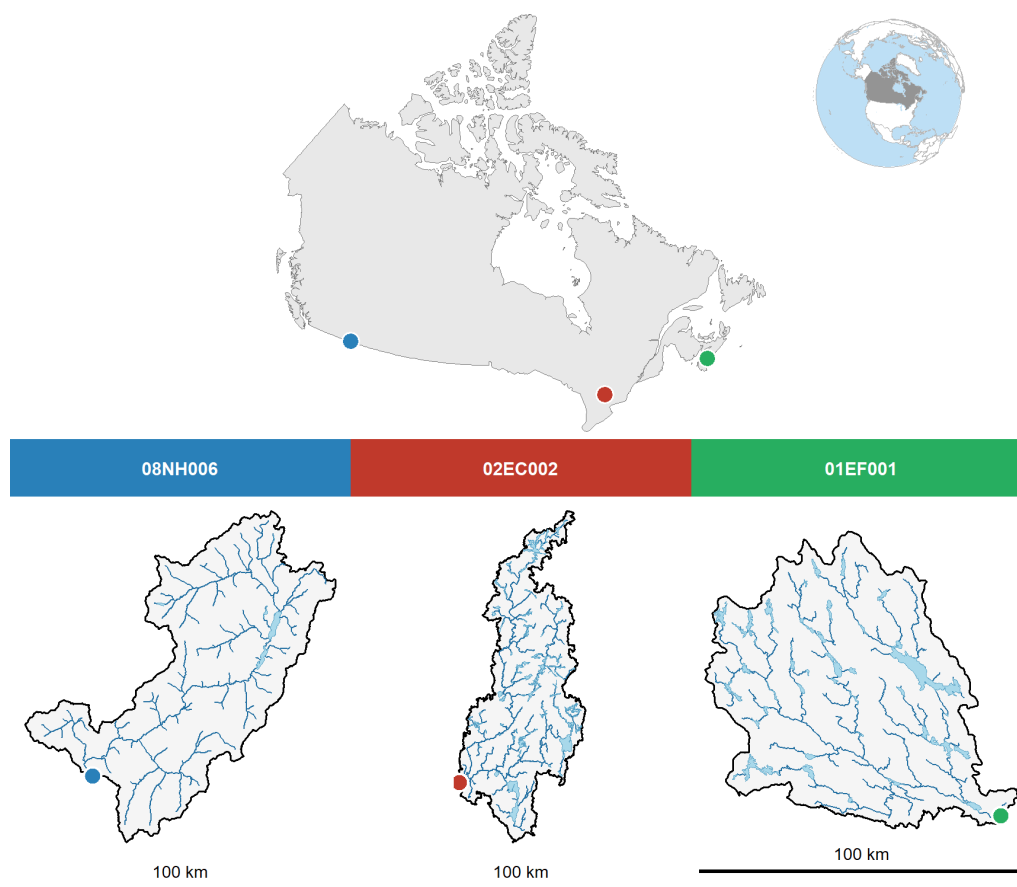


Figure 1. Geographic location of the three hydrological case studies analysed in this study. The figure shows the spatial distribution and watershed boundaries of the selected study areas.

data, including precipitation and maximum and minimum temperature, based on historical observations. This tool accounts for the variability in climatic conditions by preserving key statistical properties of precipitation and temperature such as marginal distributions, autocorrelation structures, and intermittency patterns.

– Phase 2: Long-term Continuous Simulation

4. Generate long-term forcings using the SWG, which produces synthetic time series of daily meteorological variables (e.g., precipitation and max/min daily temperature) for an extended period, spanning greater than 1000 years. This step ensures sufficient data for a robust non-parametric flood frequency analysis.
5. Simulate long-term continuous discharges using the hydrological model. The synthetic weather data generated by the SWG is used to drive the process-based hydrological model, simulating long-term streamflow for the watershed of interest.

6. Generate corresponding error realisations using the REM. The REM is applied to introduce stochastic error realisations into the simulated streamflow. This step adds probabilistic uncertainty to the hydrological model predictions, reflecting the inherent errors in model output.
7. Apply flood estimate uncertainty analysis. The resulting synthetic annual maxima, enhanced by uncertainty bounds, are ranked and used to compute flood frequency without assumptions or need of a specific parametric distribution. The annual exceedance probabilities are calculated using the Weibull plotting position formula, and the multi-realisation flood frequency curves illustrate the relationship between flood magnitude and return period, along with the associated uncertainties.

Figure 2 provides a schematic representation of the UQ-flood framework. The figure is divided into two phases: (1) the Model Setup and Parameter Estimation phase (Steps 1–3) and (2) the Long-Term Continuous Simulation phase (Steps 4–7). These steps collectively allow the computation of low-exceedance-probability flow magnitudes that explicitly ac-

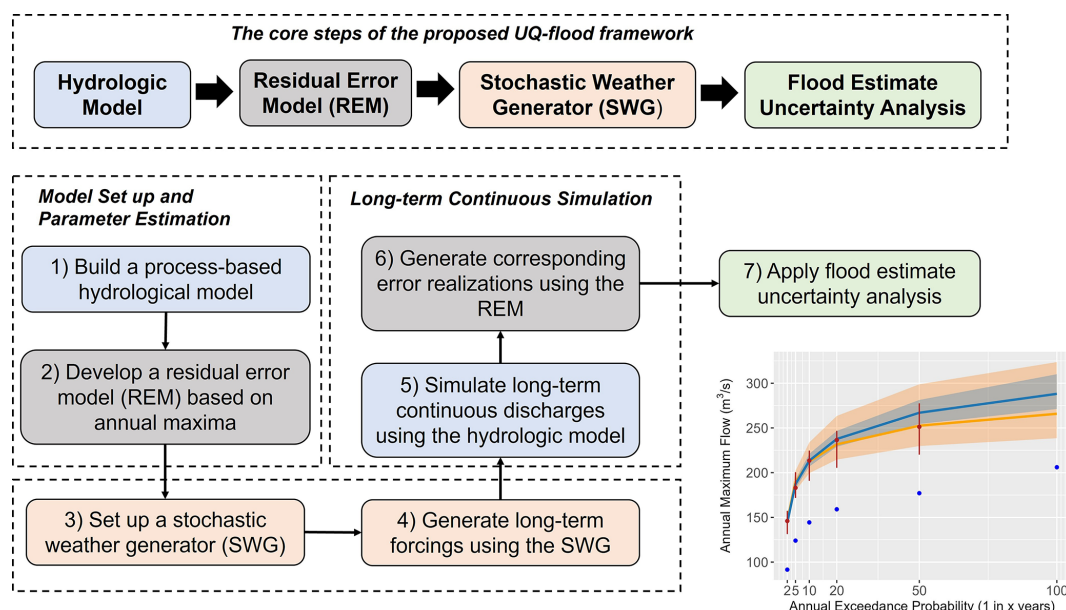


Figure 2. Conceptual diagram of the proposed UQ-flood (Residual Error Model – Flood Frequency Analysis) framework.

count for weather variability and uncertainty in hydrological modelling. This workflow ensures that uncertainties at all stages – model predictions, weather variability, and statistical error – are propagated into the final flood frequency analysis.

3.1 Hydrologic Model Development

The Hydrologiska Byråns Vattenbalansavdelning – Environment Canada (HBV-EC) model (Hamilton et al., 2000) was used to simulate watershed streamflow. A lumped representation of HBV-EC was implemented within the Raven Hydrological Modelling Framework version 3.8 (Craig et al., 2020). The HBV-EC model conceptualises catchments as a soil moisture zone atop two stacked buckets, representing upper and lower storage layers. Its structure includes three primary routines: a snow routine, soil routine, and runoff generation routine (Hamilton et al., 2000). The snow routine uses a classic degree-day approach to estimate snowmelt rates. The model partitions snowmelt and precipitation into evapotranspiration and runoff based on water and energy balance principles. Runoff is divided into surface and subsurface flow, which is further partitioned between the upper and lower buckets according to soil moisture dynamics (Seibert and Vis, 2012). A lumped version of HBV-EC was used to simulate the average temporal dynamic of catchment behaviour without requiring detailed spatial information. HBV-EC was selected due to its demonstrated strong performance in Canadian landscape (Beck et al., 2016; Stahl et al., 2008; Zégre et al., 2010), its widespread use for flood simulations (Fischer and Schumann, 2021; Sikorska et al., 2015), its parsimony, ease of implementation, and its computational efficiency (Seibert and Bergström, 2022).

The model was run using daily time series of measured discharge, precipitation, maximum and minimum temperature, which were sourced from Environment Canada. The HBV-EC models were calibrated to a truncated discharge dataset using a combination of manual and automated approaches. Manual calibration followed a stepwise process: (1) parameters controlling the long-term water balance were adjusted to achieve volumetric flow simulations; (2) parameters governing snowpack process were calibrated to accurately simulate the freshet; (3) parameters influencing soil moisture dynamics were refined to improve recession and baseflow representation. Once an acceptable parameter set was identified through manual calibration, the Dynamically Dimensioned Search (DDS) algorithm (Tolson and Shoemaker, 2008) was employed for further optimisation. The objective function minimised the daily discharge Kling-Gupta Efficiency (Gupta et al., 2009) often the last 30 years to ensure the best fit between simulated and observed hydrographs. The final set of parameters was evaluated against the long-term water balance, hydrographs, flow duration curves, and peak flows. Across all experiments, HBV calibration used only a 30-year daily streamflow subset.

3.2 Residual Error Modelling

The REM approach is a tool for propagating uncertainty into hydrological model predictions. It achieves this by incorporating samples of model error into deterministic predictions (Farmer and Vogel, 2016). REM combines deterministic predictions from process-based hydrologic models with stochastic components that characterise the uncertainties in model predictions (Montanari and Koutsoyiannis, 2012). This inte-

gration is accomplished by leveraging the statistical properties of the observed residual error, defined as the difference between observed and simulated streamflow (Vogel, 2017). By effectively characterising and modelling these residuals, the REM approach enables the generation of probabilistic streamflow estimates, accounting for uncertainties inherent in deterministic model outputs (Honti et al., 2013). REM characterises residual uncertainty as the discrepancy between simulations and observations. This residual term implicitly reflects the combined effects of forcing uncertainty, parameter uncertainty, and structural model error, without separating their individual contributions. This formulation is consistent with established error-modelling frameworks in hydrology (Li et al., 2016; McInerney et al., 2017).

In this study, the residual error model is developed for the annual maxima, aligning with the requirements of flood frequency analysis. While much of the literature has focused on REM applications at the daily streamflow – where model errors are often non-normal, heteroscedastic, and autocorrelated – our approach focuses on modelling these properties for annual maxima. The statistical properties of annual maxima residuals require careful treatment to avoid biased estimates of extremes.

The selection of the REM structure was guided by diagnostic analyses of the statistical properties of the raw residuals, including variance behaviour, temporal dependence, and distributional characteristics. To address the heteroscedasticity – where errors tend to increase with larger streamflow – we apply a Box–Cox transformation (Box and Cox, 1964) with a power parameter fixed at 0.2, following the recommendations of McInerney et al. (2017). The innovation, or random component of the REM, follows a Gaussian distribution with a flow-dependent residual mean (Li et al., 2016). The parameters of REM were inferred using the method-of-moments (Hazelton, 2011). For the detailed REM formulation, including the model equations, readers are referred to Hunter et al. (2021) and Romero-Cuellar et al. (2024).

3.3 Stochastic Weather Generator (SWG)

In this study, we employed CoSMoS (Complete Stochastic Modelling Solution) (Papalexiou, 2018) as the stochastic weather generator (SWG). CoSMoS is an R package designed for the stochastic simulation of univariate, multivariate, or random field non-Gaussian time series. It implements a flexible framework that unified, extends, and improves the theory of stochastic modelling for hydroclimatic process, preserving key statistical characteristics such as marginal distributions, autocorrelation structures, and intermittency (Papalexiou, 2018). The core assumption underlying CoSMoS is that any process can be generated by transforming a parent Gaussian process.

For this study, we inferred the parameters of the generalized gamma distribution, autocorrelation structure, and dry-period distribution of daily precipitation using 30 years

of gauge-based observations, with statistics estimated separately for each calendar month. Similarly, for maximum and minimum temperatures, we estimated the monthly marginal distributions and autocorrelation structures. Using the inferred parameters, CoSMoS was used to generate long-term (e.g., 1000 synthetic years) daily time series of precipitation, maximum temperature, and minimum temperature. These synthetic meteorological forcings were then used to drive the hydrologic model, enabling the simulation of annual maximum flows and the estimation of flood frequency distributions.

To adapt CoSMoS for flood frequency purposes, we implemented two key modifications: (1) a bootstrap-based smoothing strategy across monthly boundaries to address abrupt discontinuities in statistical properties, and (2) the introduction of physical constraints on extreme precipitation to prevent unrealistically long-tailed behaviour in the generalized gamma distribution. These constraints help avoid infinite or implausible values in simulated extremes. Full details of these modifications are provided in the Supplement (Sect. S2).

3.4 Process-based Flood Frequency Analysis

Following calibration of the hydrologic model, fitting of the stochastic weather generator (SWG), and inference of the residual error model (REM) parameters, the process-based flood-frequency analysis proceeds in two stages. First, the SWG generates 1000 years of synthetic meteorological forcings, which are transformed into streamflow using the calibrated hydrologic model. The annual maximum flow is then extracted from each synthetic year, producing a deterministic sequence of 1000 simulated annual maxima.

Second, the REM is applied to each simulated annual maximum to generate 1000 residual-error realizations. This procedure produces 1000 REM-corrected annual-maximum sequences, each containing 1000 years of flood values. For each corrected sequence, the annual maxima are ranked and assigned annual exceedance probabilities using the Weibull plotting-position formula. Flood quantiles are then estimated for the selected return periods, resulting in an ensemble of 1000 flood-frequency curves.

The central UQ-flood estimate at each return period is obtained from the median of the ensemble, while the 95 % predictive interval is defined by the 2.5th and 97.5th percentiles. This interval represents variability across the residual-error realizations, conditional on the synthetic meteorological sequence, calibrated hydrologic model, fitted SWG, and selected REM formulation.

3.5 At-site Statistical Flood Frequency Analysis

A Bayesian at-site flood-frequency analysis based on the Generalized Extreme Value (GEV) distribution was used as a secondary statistical benchmark for the central flood-quantile

estimates. Long-record empirical annual-maximum-flow estimates remained the primary observational benchmark. The GEV distribution was selected because it is grounded in extreme-value theory and is widely used to model annual maximum flows in hydrologic applications (Coles, 2001; Jenkinson, 1955; Vogel and Wilson, 1996; Zaghoul et al., 2020).

The GEV distribution was fitted to the observed annual maxima under two data configurations: the full available record and the same 30-year record used to develop UQ-flood. Bayesian inference was used to characterize uncertainty in the GEV parameters and corresponding flood quantiles (Liang et al., 2012; Parkes and Demeritt, 2016). Markov chain Monte Carlo sampling was applied to draw from the joint posterior distribution of the GEV location, scale, and shape parameters. Posterior mean flood quantiles were used as the central estimates, and the 2.5th and 97.5th percentiles of the posterior flood-quantile distributions defined the 95 % credible intervals.

The analysis was implemented using the *extRemes* R package (Gilleland and Katz, 2016). The adequacy of the fitted GEV distributions was evaluated using quantile plots, probability plots, and return-level plots for each watershed under both the short-record and long-record configurations. The diagnostics did not indicate important concerns with the fitted GEV models. The complete diagnostic results are presented in Figs. S2–S7 of the Supplement.

Central flood-quantile estimates were evaluated at return periods of $T = 2, 5, 10, 20, 50, 100$ years. For each return period, the interval width was calculated as:

$$UR_T = q_T^{97.5} - q_T^{2.5} \quad (1)$$

Where $q_T^{97.5}$ and $q_T^{2.5}$ denote the upper and lower limits, respectively, of the 95 % interval for the flood quantile associated with return period T .

The GEV and UQ-flood intervals represent different conditional uncertainty components. The Bayesian GEV credible intervals primarily characterize sampling and parameter uncertainty conditional on the observed annual-maximum sample and selected statistical model. In contrast, the UQ-flood intervals represent predictive variability across residual-error realizations conditional on the calibrated hydrologic model, fitted stochastic weather generator, and selected REM formulation. Consequently, their widths were not compared as equivalent measures of precision or performance. Instead, the GEV results were used to provide statistical context for evaluating the central UQ-flood estimates against the long-record observational benchmarks.

3.6 Confidence Interval for Discharge Quantiles

This study quantifies uncertainty in discharge quantiles associated with specified annual exceedance probabilities (AEPs), rather than uncertainty in plotting positions or order statistics. The focus is therefore on vertical uncertainty – i.e.,

uncertainty in discharge for a fixed return period – which is the quantity most relevant for flood-risk assessment and engineering design.

To estimate confidence intervals for discharge quantiles, we adopt an analytical approach based on fitting parametric probability distributions to annual maximum flow (AMF) data. Several candidate distributions (e.g., Weibull, exponential, gamma, and lognormal) are fitted using maximum likelihood estimation. Model selection is guided by a combination of visual diagnostics (density plots, $Q-Q$ plots, and cumulative distribution function comparisons) and statistical criteria, including the Akaike Information Criterion (AIC) and goodness-of-fit statistics. The selected distribution provides the basis for estimating uncertainty in discharge quantiles corresponding to target AEPs.

For a given AEP, the corresponding non-exceedance probability is defined as:

$$p = \left(1 - \frac{1}{\text{AEP}}\right)(N + 1) \quad (2)$$

Where N is the sample size and AEP is expressed in years. The uncertainty in this probability estimate due to finite sample size is modelled using the beta distribution, consistent with the analytical framework of Baà et al. (2001). The lower and upper bounds of the 95 % confidence interval are computed as:

$$\begin{aligned} x_{0.05} &= q_{\text{beta}}(0.025, p, N - p + 1) \\ x_{0.95} &= q_{\text{beta}}(0.975, p, N - p + 1) \end{aligned} \quad (3)$$

These bounds are then transformed into flow quantiles using the cumulative distribution function (CDF) of the selected parametric model:

$$\begin{aligned} Q_{0.05} &= F^{-1}(x_{0.05}) \\ Q_{0.95} &= F^{-1}(x_{0.95}) \end{aligned} \quad (4)$$

where F^{-1} is the inverse CDF (quantile function) of the fitted distribution. This procedure yields confidence intervals for discharge quantiles that explicitly reflect sampling uncertainty conditional on the assumed statistical model. It provides a transparent, closed-form alternative to resampling-based methods and is well suited for comparative analyses across multiple basins. We emphasize that this approach differs conceptually from methods that quantify uncertainty in exceedance probabilities or order statistics (horizontal uncertainty), such as fractional order statistics (e.g., Serinaldi, 2009). While such approaches are valuable – particularly for estimating uncertainty beyond the observed sample maximum – the present study prioritizes uncertainty in discharge for fixed design return periods.

3.7 Numerical Experiment Configuration

To evaluate the proposed UQ-flood framework, we designed a numerical experiment focused on two questions: (1)

whether the central flood-quantile estimates obtained using 30 years of observations are consistent with long-record observational benchmarks, and (2) how explicitly accounting for hydrologic-model error through the residual error model affects process-based flood estimates.

Long-record empirical annual-maximum-flow estimates were used as the primary benchmark. A Bayesian GEV analysis was retained as a secondary statistical benchmark for the central flood-quantile estimates. Because the UQ-flood and GEV intervals characterize different uncertainty components, their widths were not compared as equivalent measures of precision or performance.

The evaluation consists of two main components:

1. Evaluation under different observational record lengths

UQ-flood was developed using 30 years of observed meteorological and streamflow data. Its central flood-quantile estimates were evaluated against:

- Empirical annual-maximum-flow estimates derived from the full available observational record.
- Bayesian GEV estimates fitted to the full observational record.
- Bayesian GEV estimates fitted to the same 30-year annual-maximum series used to develop UQ-flood.

This experimental design evaluates whether UQ-flood estimates developed from a limited observational period remain consistent with the long-record empirical benchmark. The long- and short-record GEV analyses provide statistical context for interpreting the effects of observational record length on the central flood-quantile estimates. The comparison does not imply that the UQ-flood and GEV uncertainty intervals represent the same uncertainty components.

2. Evaluation of process-based simulation without residual error modelling

To assess the contribution of the REM, we conducted an additional experiment in which flood-frequency estimates were derived directly from annual maximum flows generated by the hydrologic model and stochastic meteorological inputs, without residual-error correction. This configuration is referred to as the process-based simulation without REM (det-SIM).

Comparison of these uncorrected estimates with the UQ-flood estimates and long-record observational benchmark was used to identify systematic discrepancies in the deterministic process-based simulations and evaluate the extent to which the REM corrects these discrepancies at the annual-maximum scale. Together, these experiments evaluate the consistency of the central UQ-flood estimates with long-record observations and isolate the contribution of residual-error modelling to process-based flood-frequency estimation.

For the Black River and Moyie River watersheds, the HBV-EC hydrologic model, CoSMoS stochastic weather generator, and residual error model were calibrated or inferred using observations from 1 January 1991 to 31 December 2020. For the Lahave River watershed, the corresponding period extended from 1 January 1992 to 31 December 2021. These periods represented the most recent complete 30-year observational records available for the respective watersheds. For each watershed, the same period was also used for the short-record GEV analysis, ensuring consistency across the modelling and statistical comparisons.

4 Results

This section evaluates the UQ-flood framework across three case-study watersheds. Section 4.1 presents a detailed assessment for the Black River watershed, including comparisons with the long-record observational benchmark, GEV estimates based on the full and 30-year records, and the process-based simulation without REM. Section 4.2 applies the same evaluation to the Moyie River and Lahave River watersheds to examine whether the central UQ-flood estimates remain consistent with the observational benchmarks under contrasting hydrologic conditions.

4.1 Flood Frequency Estimates for the Black River Watershed

4.1.1 Evaluation against Observational and Statistical Benchmarks

Figure 3 compares the UQ-flood estimates with the long-record empirical annual-maximum-flow estimates (AMAX), Bayesian GEV estimates fitted to the long and short observational records, and the process-based simulation without REM (det-SIM). The upper panel presents the GEV analysis based on the full 108-year record, whereas the lower panel presents the GEV analysis based on the same 30-year period used to develop UQ-flood. The UQ-flood results are identical in both panels and are repeated to facilitate comparison with the two GEV configurations.

The central UQ-flood estimates remain consistent with the long-record observational benchmark across the evaluated return periods, despite the framework being calibrated and inferred using only 30 years of meteorological and streamflow data. At the 50- and 100-year return periods, the UQ-flood estimates remain within the confidence intervals for the corresponding long-record discharge quantiles. The long-record GEV estimates also generally follow the empirical flood-frequency relationship, while differences among the central estimates vary with return period. Numerical estimates for selected return periods are provided in Table S1 in the Supplement.

The short-record GEV analysis is more sensitive to extrapolation at high return periods, with its central estimate diverg-

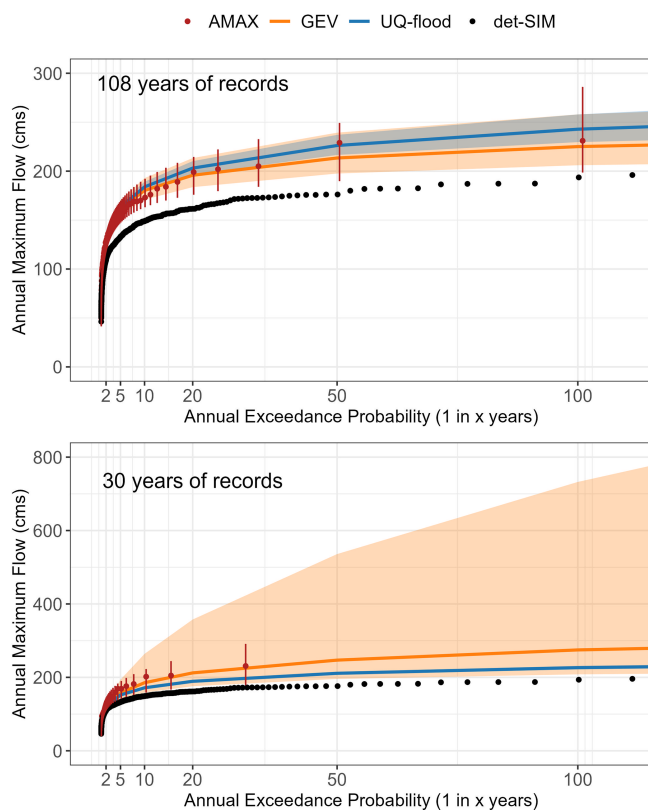


Figure 3. Flood frequency estimates and associated 95 % uncertainty intervals for the Black River watershed derived using the statistical GEV approach and the UQ-flood framework. The observed annual maximum discharge (AMAX; red) distribution, shown with confidence intervals for discharge quantiles, and the deterministic simulation output (without error model) (det-SIM; black points) are included for reference. The top panel shows GEV results using long-term records; the bottom panel uses short records. The UQ-flood framework uses only the 30-year record in both cases.

ing progressively from the long-record observational benchmark. This result illustrates the influence of the selected 30-year annual-maximum sample on the fitted GEV distribution. In contrast, UQ-flood incorporates information from the meteorological record, the hydrologic model, and the annual-maximum residual relationship. The comparison therefore evaluates whether this process-based modelling chain produces central flood-quantile estimates consistent with the long-record benchmark, rather than whether its uncertainty interval is narrower than the GEV interval.

The UQ-flood and GEV uncertainty intervals should be interpreted separately because they represent different conditional uncertainty components. The UQ-flood interval describes predictive variability across residual-error realizations, conditional on the calibrated hydrologic model, fitted weather generator, selected REM structure, and available calibration data. The Bayesian GEV interval primarily represents sampling and parameter uncertainty conditional on

the observed annual-maximum sample and selected statistical model. Consequently, differences in interval width are not interpreted as evidence of greater precision or superior performance. The UQ-flood interval has the same width in the upper and lower panels; its apparently different visual width results solely from the broader y-axis scale in the lower panel.

Finally, the process-based simulation without REM systematically underestimates the long-record annual-maximum estimates. Applying the REM shifts the process-based flood-frequency curve toward the observational benchmark, demonstrating the importance of representing hydrologic-model discrepancies at the annual-maximum scale. Thus, the principal result for Black River is that the REM corrects systematic bias in the uncorrected process-based simulation and produces central flood-quantile estimates that remain consistent with the long-record observations.

4.1.2 Simulation-length sensitivity analysis

A sensitivity analysis was conducted to examine whether the length of the synthetic streamflow sequence systematically controls the width of the UQ-flood interval. Simulated series of 100, 200, 500, 800, 1000, 2000 and 3000 years were evaluated for the 50- and 100-year flood quantiles. For each series length, 1000 residual-error realizations were generated, with each realization containing the specified number of annual maxima. The interval width, calculated as the difference between the 97.5th and 2.5th percentiles of the flood-quantile estimates across the ensemble. Figure 4 shows that the UQ-flood interval width is sensitive to the synthetic-series length, particularly for shorter simulations.

The sensitivity analysis shows that the UQ-flood interval width decreases substantially as the synthetic-series length increases from 100 to approximately 1000–2000 years. For both the 50- and 100-year flood quantiles, the interval width declines from approximately $2.9 \text{ m}^3 \text{ s}^{-1}$ at 100 years to approximately $1.7\text{--}1.8 \text{ m}^3 \text{ s}^{-1}$ at 1000–2000 years. Beyond 1000 years, the changes are small, with a slight increase at 3000 years. The nearly overlapping curves indicate that simulation length affects the 50- and 100-year flood intervals similarly. Overall, the results suggest that shorter synthetic sequences introduce greater finite-sample variability, whereas the flood-quantile intervals become relatively stable at sequence lengths of approximately 1000 years or more. This stabilization reflects reduced numerical sampling variability conditional on the fitted UQ-flood modelling chain and should not be interpreted as adding observational information or reducing all sources of uncertainty about the watershed.

4.2 Application to Additional Watersheds

The UQ-flood framework was further evaluated for the Moyie River and Lahave River watersheds, shown in the

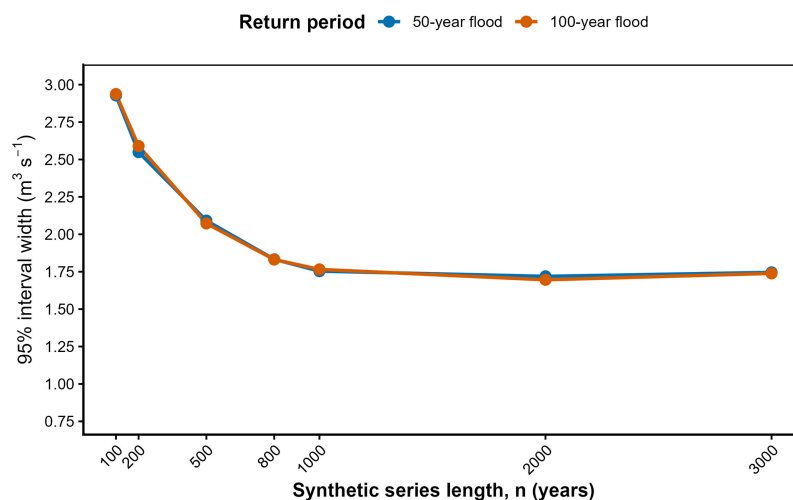


Figure 4. Sensitivity of the UQ-flood 95 % interval width to simulated-series length for the 50- and 100-year flood quantiles in the Black River watershed. Interval width is defined as the difference between the 97.5th and 2.5th quantiles across the predictive ensemble.

left and right panels of Fig. 5, respectively. As in the Black River analysis, the long-record empirical annual-maximum estimates provide the primary benchmark. Bayesian GEV estimates based on the full and 30-year records provide secondary statistical benchmarks, while the process-based simulation without REM is included to assess the contribution of residual-error correction. UQ-flood was developed using 30 years of meteorological and streamflow observations in both watersheds.

The central UQ-flood estimates remain within the confidence intervals for the long-record discharge quantiles across the evaluated return periods. However, neither UQ-flood nor the long-record GEV is uniformly closest to the empirical estimates. For Lahave River, UQ-flood is closer to the empirical estimate at the 50-year return period, whereas the long-record GEV is closer at the 100-year return period. For Moyie River, the two approaches produce similar estimates at lower return periods, while the long-record GEV is closer to the empirical estimate at the 50-year return period. These results are notable because UQ-flood uses only 30 years of observations, whereas the long-record GEV uses the full available annual-maximum series. The corresponding numerical estimates are provided in the Supplement (Table S1).

The UQ-flood and GEV uncertainty intervals represent different conditional uncertainty components, and their widths are therefore not compared as equivalent measures of precision or performance. Instead, the evaluation focuses on whether the central estimates are consistent with the long-record observational benchmarks. The confidence intervals for the empirical discharge quantiles are particularly important at high return periods, where the observed plotting positions are affected by greater sampling uncertainty.

For both watersheds, the process-based simulations without REM underestimate the long-record empirical flood quantiles. Applying the REM shifts the process-based esti-

mates toward the observational benchmarks, demonstrating the importance of representing hydrologic-model discrepancies at the annual-maximum scale. Overall, the additional case studies show that UQ-flood produces central estimates consistent with the observational confidence intervals and that the REM corrects systematic biases in the uncorrected process-based simulations. However, the relative proximity of UQ-flood and GEV to the empirical estimates varies by watershed and return period, and neither approach is uniformly closest across all cases.

5 Discussion

The findings of this study should be interpreted in the context of the short-sample problem in flood frequency analysis (FFA). As discussed in the Introduction, limited annual maximum flow records can lead to substantial uncertainty in rare flood quantile estimates, with confidence intervals that may be too wide to support practical design and planning decisions. Existing approaches address this limitation by incorporating additional information from historical or paleoflood records, leveraging spatial information through regional flood frequency analysis, or generating synthetic samples through continuous simulation. UQ-flood contributes to the latter approach by combining process-based hydrologic simulation with explicit bias correction and residual uncertainty propagation at the annual maximum scale. Rather than replacing historical-data or regional approaches, the framework offers a complementary, process-consistent alternative for situations in which local records are short and uncertainty intervals from conventional statistical FFA become impractically wide.

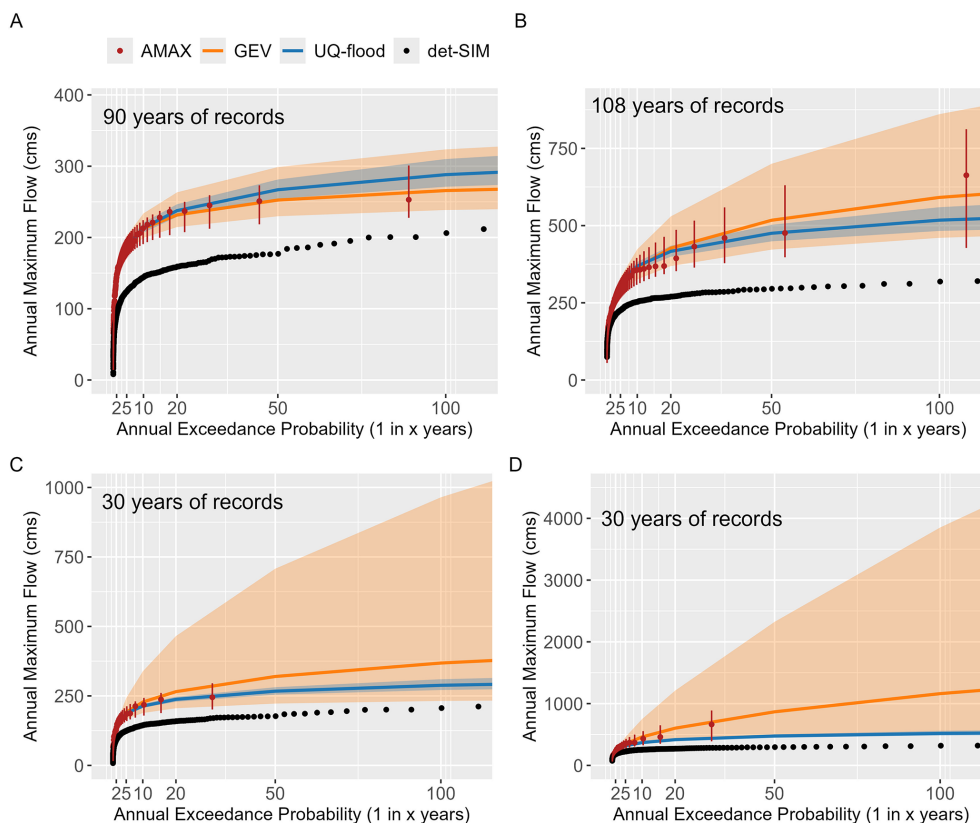


Figure 5. Flood frequency estimates and associated 95 % uncertainty intervals for the Moyie River (**A**, **C**) and Lahave River (**B**, **D**) derived using the statistical GEV approach and the UQ-flood framework. The observed annual maximum discharge (AMAX; red) distribution, shown with confidence intervals for discharge quantiles, and the deterministic simulation output (without error model) (det-SIM; black points) are included for reference. Panels (**A**) and (**B**) show GEV results using long-term records; panels (**C**) and (**D**) use short records. The UQ-flood framework uses only the 30-year record in both cases.

5.1 Placing the UQ-flood Framework in Context

Uncertainty is an established consideration in flood frequency analysis, and conventional statistical methods provide confidence or credible intervals for estimated flood quantiles (England et al., 2018). These intervals are valuable for characterizing sampling and parameter uncertainty conditional on the observed flood sample and selected probability model, but they do not necessarily represent uncertainty arising from a process-based modelling chain. In process-based FFA, flood estimates are additionally affected by the representation of meteorological variability, hydrologic-model structure and parameters, antecedent conditions, and errors in simulated flood peaks; the relative importance of these components may also vary with return period and watershed characteristics (Arnaud et al., 2017; Cameron et al., 2000; Newman et al., 2021). Process-based simulation therefore does not eliminate uncertainty associated with short observational records but redistributes it across a broader set of modelling assumptions and components. This distinction is important when interpreting the present results: the UQ-flood and Bayesian GEV intervals characterize different con-

ditional uncertainty components and should not be compared directly as equivalent measures of overall precision. Accordingly, the GEV analysis is retained as a secondary statistical benchmark, while the primary evaluation focuses on whether the central UQ-flood estimates remain consistent with the long-record observational benchmarks and whether the residual error model corrects systematic biases in the process-based flood estimates.

The UQ-flood framework presented in this study offers a complementary approach to existing methods by integrating process-based hydrologic simulation with a residual error model (REM) and a stochastic weather generator. This integration supports a shift towards process-based uncertainty quantification that is consistent with hydrologic processes. Rather than replacing existing methods, UQ-flood aims to enhance uncertainty characterisation by propagating uncertainty from model inputs through to flood quantile estimates. In this context, incorporating error models into continuous simulation frameworks may help improve bias correction and support more transparent flood risk estimation.

5.2 Annual-Maximum Residual Error Modelling in Process-Based FFA

A key contribution of UQ-flood is the integration of a process-based hydrologic model, a stochastic weather generator, and a residual error model developed specifically for annual maximum flows. Although these components have been used separately in previous flood-frequency studies, their integration allows systematic hydrologic-model discrepancies to be corrected at the same scale as the target design variable.

The annual-maximum formulation addresses an important mismatch in process-based FFA. Hydrologic models are commonly calibrated using daily streamflow metrics that emphasize overall hydrograph behaviour, water balance, and seasonal dynamics. However, satisfactory daily-flow performance does not guarantee unbiased simulation of annual flood peaks, which may be particularly sensitive to antecedent conditions, threshold processes, snowmelt–rainfall interactions, and upper-tail behaviour. This limitation was evident in the simulations without the REM, which systematically underestimated flood quantiles across the study watersheds. By modelling the residual relationship between observed and simulated annual maxima, the REM corrects these systematic discrepancies and represents residual predictive variability at the scale directly relevant to flood-frequency estimation.

UQ-flood uses a sequential modelling structure in which the hydrologic model, stochastic weather generator, and REM are developed separately. This structure is statistically less complex than fully joint Bayesian approaches that simultaneously infer parameters across the complete modelling chain. However, UQ-flood should not be interpreted as free from subjective or user-defined decisions. Hydrologic-model selection and calibration, weather-generator selection and configuration, REM specification, and transformation choice can all affect the resulting flood estimates. Moreover, long continuous simulations can remain computationally demanding.

The Box–Cox transformation parameter was fixed at $\lambda = 0.2$, following previous hydrologic residual-error studies that identified this value as suitable for representing heteroscedastic streamflow errors. Nevertheless, the fixed value remains a modelling assumption, and its influence was not evaluated in this study. Future applications should assess whether the selected transformation and residual-error structure adequately represent the residual characteristics of the watershed and flood regime under consideration.

UQ-flood does not require fitting a parametric probability distribution directly to the synthetic annual-maximum series. Instead, flood quantiles are estimated empirically from the REM-corrected sequences using plotting positions. This avoids imposing a parametric form on the final synthetic flood sample, but it does not remove the assumptions embedded in the hydrologic model, weather generator, or REM. The framework should therefore be viewed as a complemen-

tary process-based approach rather than a replacement for conventional statistical FFA.

Overall, the contribution of UQ-flood lies in explicitly representing hydrologic-model error at the annual-maximum scale. The framework corrects systematic biases in deterministic process-based simulations and propagates residual predictive variability into flood-quantile estimates.

5.3 Limitations and Future Directions

UQ-flood remains conditional on the choices and assumptions within its modelling chain. The UQ-flood interval represents residual predictive variability, whereas statistical FFA intervals primarily characterize sampling and parameter uncertainty conditional on a selected probability model. Because these intervals represent different uncertainty components, their widths should not be compared as equivalent measures of overall precision.

Flood estimates are influenced by hydrologic-model structure and calibration, stochastic weather-generator selection and configuration, and residual-error-model specification. In this study, CoSMoS initially produced implausibly long-tailed precipitation extremes in very long simulations, requiring a constraint to preserve physical plausibility. UQ-flood is not restricted to CoSMoS and could use other meteorological sampling approaches, including stochastic storm transposition (Wright et al., 2020), reforecast ensemble pooling (Brunner and Slater, 2022), or convection-resolving climate simulations (Dallan et al., 2024). However, all synthetic sequences represent the climate conditions reflected in the calibration period and should not be interpreted as future-climate projections.

A core assumption of UQ-flood is that process-based hydrologic models can derive more useful information than purely statistical extrapolation from short records. That is, expert knowledge about watershed processes – such as water balance, storage, and runoff generation – enables the model to constrain future flood behavior more effectively than sampling-based uncertainty alone (Su and Tung, 2013). In this sense, UQ-flood acts as a more intelligent flood sampler, embedding physical understanding directly into the generation of extreme event ensembles.

The present analysis does not propagate uncertainty in streamflow measurements, rating curves, hydrologic-model parameters, or weather-generator parameters. These uncertainties may be important for rare floods and should be incorporated in future applications. Moreover, UQ-flood requires sufficient meteorological and streamflow observations to calibrate the modelling components and characterize annual-maximum residuals.

Transferability depends on whether the hydrologic model and meteorological generator adequately represent the dominant flood-generating processes. The modular framework can accommodate alternative lumped or distributed models, but this flexibility does not guarantee reliable performance in

different or ungauged watersheds. Applications to ungauged basins would require regionalization or parameter-transfer methods and case-specific evaluation.

The current implementation uses annual maxima, but UQ-flood is not structurally limited to this formulation. A peaks-over-threshold extension could use more high-flow information from short records but would require explicit treatment of threshold selection, event independence, declustering, exceedance frequency, and event magnitude. Future work should also use event-scale diagnostics to investigate how hydrologic-model performance, meteorological simulation, residual-error characteristics, and flood-generating mechanisms contribute to differences among watersheds.

5.4 Implications for Design and Decision-Making

The findings across the three case studies highlight the potential practical value of UQ-flood for flood risk management and engineering design. For watersheds with long flow records, UQ-flood produced flood quantile estimates consistent with those obtained using conventional statistical flood frequency analysis (FFA), while yielding narrower uncertainty intervals. Under short-record conditions, such as a 30-year record, UQ-flood also provided robust and actionable flood estimates, whereas conventional statistical FFA produced substantially wider uncertainty intervals that may be impractical for design and planning purposes. These findings suggest that UQ-flood can help address the limitations of local data scarcity, a common challenge in operational flood risk assessment.

From a practical perspective, improved characterization of uncertainty can support more informed design and investment decisions. Uncertainty intervals that are excessively wide can complicate the selection of design floods, potentially contributing to overdesign and unnecessary costs or underdesign and increased flood risk. In applications such as infrastructure planning, floodplain mapping, and insurance risk assessment, more informative uncertainty estimates can support the prioritization of investments, the evaluation of alternative design options, and the development of climate-resilient infrastructure.

UQ-flood also provides a process-based framework for interpreting and communicating flood estimates. By combining hydrologic simulation, explicit bias correction, and residual uncertainty propagation, the framework links flood quantile estimates to modeled hydrologic processes and observed model performance. This provides a complementary perspective to conventional statistical FFA, in which estimates depend primarily on the selected probability distribution and the available sample of annual maximum flows. Nevertheless, the process-based nature of UQ-flood does not eliminate uncertainty associated with model structure, parameter estimation, or the representation of hydrologic processes; these sources of uncertainty should be considered when interpreting results and applying them to engineering decisions.

Finally, the UQ-flood is conceptually aligned with the emerging design simulation approach (Fischer et al., 2025), which emphasizes process-based flood estimation to inform engineering design. Within this context, UQ-flood offers a framework for incorporating quantified uncertainty into decisions such as the selection of design floods and safety factors. Rather than relying exclusively on fixed safety margins, engineers and decision-makers can use uncertainty estimates to evaluate the robustness of alternative design choices against specified risk tolerances. The potential benefit is a more transparent and evidence-based balance between infrastructure costs and flood safety, particularly in watersheds where limited observational records constrain conventional flood frequency analysis.

6 Conclusions

Process-based Flood frequency estimates are affected by multiple sources of uncertainty, including limited observations, meteorological variability, hydrologic-model errors, parameter uncertainty, and model-structure choices. Transparent characterization of these uncertainties is important for the appropriate interpretation and use of flood estimates in engineering design and risk management.

This study introduced UQ-flood, a process-based flood-frequency framework that integrates a stochastic weather generator, a process-based hydrologic model, and a residual error model developed at the annual-maximum scale. The framework was designed to address the mismatch between hydrologic models commonly calibrated against daily streamflow and the annual flood peaks used in flood-frequency analysis. The residual error model corrects systematic discrepancies in the simulated annual maxima and propagates residual predictive variability into the resulting flood-quantile estimates.

UQ-flood was evaluated in three Canadian watersheds with contrasting hydroclimatic and physiographic characteristics. Long-record empirical annual-maximum estimates were used as the primary benchmark, while Bayesian GEV estimates based on long and 30-year records provided secondary statistical benchmarks. The principal findings are as follows:

1. The central UQ-flood estimates remained consistent with the long-record observational benchmarks when the framework was developed using only 30 years of meteorological and streamflow observations. The relative proximity of UQ-flood and GEV to the empirical estimates varied among watersheds and return periods, and neither approach was uniformly closest in every case.
2. Process-based simulation without residual-error correction produced systematic biases in the estimated flood quantiles. Applying the REM shifted the simulated

flood-frequency curves toward the long-record observational benchmarks, demonstrating the importance of accounting for hydrologic-model discrepancies at the annual-maximum scale.

3. The annual-maximum REM provided an explicit representation of residual predictive variability around the corrected process-based estimates. This scale-specific formulation targets the same variable used in engineering flood-frequency analysis rather than assuming that satisfactory daily-streamflow performance guarantees unbiased simulation of annual flood peaks.

The results do not imply that process-based simulation eliminates the information limitations associated with short observational records. Instead, UQ-flood uses the available meteorological and streamflow information through a process-based modelling chain and explicitly represents residual errors in the simulated design variable. Its estimates remain conditional on the adequacy of each component of that chain.

Overall, the results demonstrate that explicitly modelling residual errors at the annual-maximum scale can improve the consistency of process-based flood-frequency estimates with long-record observations. UQ-flood should therefore be viewed as a complementary framework for process-based FFA rather than as a replacement for conventional statistical methods.

Future work should evaluate the framework across a broader range of hydroclimatic regimes and examine uncertainty associated with hydrologic-model parameters, weather-generator parameters and structure, streamflow measurements, and alternative REM formulations. Further developments could also extend UQ-flood to peaks-over-threshold applications and investigate residual error models conditioned on flood-generating mechanisms.

Code and data availability. The stochastic weather generator CoSMoS is available for download from its Github repository: <https://github.com/TycheLab/CoSMoS> (last access: 27 October 2026; Papalexiou, 2018). The Raven hydrological modelling framework can be accessed at <https://raven.uwaterloo.ca/> (last access: 27 October 2026). Historical weather data were obtained from Environment and Climate Change Canada (ECCC) and are publicly available at <https://climate.weather.gc.ca/> (last access: 27 October 2026). Streamflow data were sourced from the Water Survey of Canada and can be downloaded via <https://dd.weather.gc.ca> (last access: 27 October 2026). The UQ-flood scripts and datasets used in the analyses presented in this paper are archived on Zenodo at <https://doi.org/10.5281/zenodo.23697697> (Romero-Cuellar et al., 2026).

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