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Non-Linear Parameter Uncertainty Propagation Across Multi-Frequency Flood Hydrographs in a Responsive Mountain Catchment

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Abstract

Quantifying predictive uncertainty in rainfall–runoff modeling is essential for reliable flood risk assessment, particularly in flash-flood-prone mountain catchments. This study evaluates a stochastic parameter uncertainty framework applied to a 3420.9 km² watershed. Parameter uncertainty was systematically propagated through HEC-HMS using Monte Carlo simulations sampled via a triangular probability density function across varying rainfall event magnitudes.

Ensemble simulations reveal a clear shift in hydrological behavior across storm intensities. Moderate events are dominated by rapid runoff generation and substantial attenuation during channel routing, whereas high-magnitude events exceed channel storage capacity, shifting the maximum flood hydrograph to a delayed secondary peak at the basin outlet, reaching up to 1391.10 m³/s.

Spatial analysis shows that relative uncertainty across upstream sub-basins increases nonlinearly before stabilizing between 15.0% and 16.95% under high-magnitude forcing. Downstream channel routing progressively attenuates relative uncertainty, reducing it to approximately 7.5% at the outlet; however, the absolute spread in peak discharge widens considerably, from 54.46 m³/s in low-intensity events to 536.20 m³/s in extreme events. These findings highlight the critical need to account for nonlinear uncertainty propagation when coupling hydrological models with downstream hydraulic frameworks (e.g., HEC-RAS) for robust floodplain management and infrastructure design.

Keywords: Stochastic Uncertainty Propagation; Rainfall–Runoff Modeling; Monte Carlo Simulation; Hydrologic Routing; Peak Discharge Uncertainty; Flood Risk Assessment.

1. Introduction

Accelerated hydro-climatic shifts have systematically altered the frequency, magnitude, and predictability of extreme flood events globally (Hall et al., 2014; Burn et al., 2016; IPCC, 2021). Flash-prone mountainous catchments are exceptionally vulnerable to these perturbations due to steep topographic gradients, high drainage densities, and brief times of concentration (T_c) (Merz and Blöschl, 2008; Marchi et al., 2010). In these responsive regimes, high-intensity or extended multi-day precipitation inputs rapidly exhaust initial abstraction capacities, causing a swift transition from infiltration-excess (Horton) to saturation-excess (Dunne) overland flow mechanisms (Dunne and Black, 1970; Chow et al., 1988). When these fast-moving flood waves translate down the drainage network into alluvial plains, they present severe risks to hydraulic infrastructure, agricultural sectors, and socio-economic stability (IPCC, 2021; Blöschl et al., 2019). Minimizing these risks requires accurate design flood estimates and robust boundary-condition forecasting across a range of recurrence intervals (England et al., 2019).

To simulate these hazards, risk management frameworks rely heavily on coupled modeling chains. Typically, a semi-distributed rainfall–runoff model (e.g., HEC-HMS) translates meteorological design storms into upstream flow hydrographs, which are subsequently routed through downstream channels using unsteady hydrodynamic models (e.g., 1D/2D HEC-RAS) (Scharffenberg and Fleming, 2021; USACE, 2023). However, the reliability of these coupled frameworks is fundamentally limited by structural and parametric uncertainty (Beven, 1993; Beven and Binley, 1992). In practical engineering workflows, flood frequency analysis (FFA) and subsequent rainfall–runoff transformations are often executed deterministically (Gumbel, 1958; England et al., 2019). This traditional approach completely ignores the substantial uncertainties embedded within the modeling chain—specifically regarding precipitation disaggregation, initial soil moisture states, channel routing coefficients, and empirical parameterization (such as the SCS Curve Number, CN) (Moradkhani et al., 2005; Gupta et al., 2009). Consequently, relying on a single deterministic design hydrograph introduces a false sense of security into engineering designs, as minor variations in critical sub-basin parameters can cause large, non-linear fluctuations in downstream peak flows (Beven and Binley, 1992; Pappenberger et al., 2005).

While the scientific community has leveraged advanced stochastic frameworks—such as Generalized Likelihood Uncertainty Estimation (GLUE) and Markov Chain Monte Carlo (MCMC) simulations—to quantify hydrologic variance (Beven and Binley, 1992; Vrugt et al., 2003; Moradkhani et al., 2005), a critical research gap persists regarding how parameter uncertainty propagates across different return periods within complex, multi-basin channel networks. Most uncertainty studies evaluate sensitivity under isolated historical events or focus exclusively on variance scaling at a single catchment outlet (Aronica et al., 2002; Blazkova and Beven, 2009). Consequently, the spatiotemporal mechanics governing how a river network alters upstream parameter variance remain poorly understood. Specifically, research has yet to fully explain whether drainage networks operate as variance filters or variance amplifiers as meteorological forcing grows more extreme, and how wave translation lags interact with sub-basin hydrograph synchronization across variable recurrence intervals (Merz and Blöschl, 2008; Pappenberger et al., 2005).

To address these limitations, this study introduces a generalized stochastic parameter uncertainty framework within a complex, highly responsive catchment (3420.9 km²). Rather than relying on deterministic assumptions, parameter uncertainty was explicitly mapped across hillslope components using a stochastic triangular probability density function within a Monte Carlo simulation matrix ($n = 5,000$).

The resulting ensemble hydrographs were systematically analyzed across a spectrum of storm event magnitudes at each sub-basin outlet, channel confluence, and major catchment node using five statistical descriptors: mean flow, ± 1 standard deviation bounds, and absolute maximum–minimum envelopes.

This analysis aimed to:

- A. Identify the dominant spatial sources and scaling of discharge uncertainty across sub-basins,
- B. Assess the temporal evolution and multi-peak hydrograph behavior during prolonged runoff events, and
- C. Evaluate the channel network’s capacity to attenuate or amplify relative and absolute predictive uncertainty under varying hydrologic forcing.

2. Methodology

2.1. Subbasin Disaggregation and Topology

As shown in Fig. a, the 3420.9 km² catchment was discretized into five discrete subbasins (**SB1–SB5**) to account for spatial heterogeneity in terrain, soil hydraulics, and land cover. **SB5** (1037.4 km²), **SB3** (969.2 km²), and **SB2** (758.9 km²) constitute the primary headwater yield contributors, while **SB1** (633.5 km²) and **SB4** (21.9 km²) represent eastern and micro-scale lateral drainage zones, respectively. Each subbasin computes hillslope abstraction and transform kinetics independently before discharging hydrographs downstream. This spatial subbasin layout governs initial loss generation, surface runoff translation, and volumetric yield across the watershed.

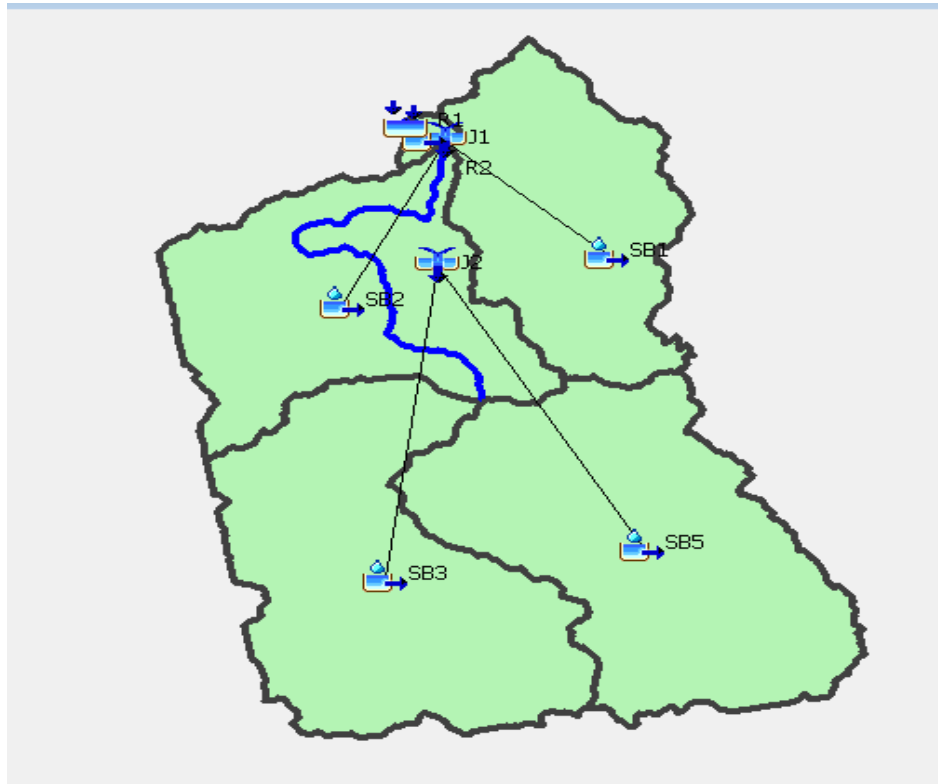


Fig. a. Spatial discretization and layout of the five constituent subbasins (SB1–SB5) within the study catchment. Refer to this figure for subbasin boundaries and spatial arrangement.

2.2 Statistical Propagation and Hydrograph Envelopes

To evaluate the downstream movement of parameter variance through the drainage channel network, the simulated multi-frequency ensemble outputs were summarized using five core statistical descriptors tracked at every channel confluence and primary outlet node (Sink-1):

1. Ensemble Mean Hydrograph μ : The expected central flow trend.
2. Upper Variance Margin $\mu + \sigma$: Proportional reduction boundary at one standard deviation (σ)
3. Lower Variance Margin $\mu - \sigma$: Proportional reduction boundary at one standard deviation σ
4. Absolute Envelope Maximum $Q_{\max}$: Extreme upper bound representing worst-case flood peak discharge.
5. Absolute Envelope Minimum $Q_{\min}$: Conservative lower limit representing lowest generated surface runoff.

Relative variance transformation across scale was evaluated at hydrograph crest coordinates utilizing the coefficient of variation metric:

$$\text{Relative Predictive Uncertainty (\%)} = \left(\frac{\sigma}{\mu} \right) \times 100\%$$

3. Results and Discussion

3.1. Stochastic Uncertainty Analysis and Temporal Wave Progression

The statistical distribution of predictive variance generated via Monte Carlo sampling of the SCS Curve Number (Triangular PDF) is presented below, broken down by individual return periods, along with their corresponding graphical plots.

3.1.1. The High-Frequency 2-Year Recurrence Boundary

The sharp, flash-like response of the upstream catchments under a 2-year storm scenario is compiled in **Table 1** and visualized in the multi-panel composite layout of **Figure 1**.

Table 1: Peak Flow Uncertainty Vector and Envelopes (2-Year event)

Location	Peak Time	Mean Flow μ (m ³ /s)	Std Dev σ (m ³ /s)	Relative Uncertainty (%)	Absolute Spread (Q _{max} – Q _{min} , m ³ /s)
SB1	17 Jun, 18:00	66.413	6.969	10.49%	29.915
SB2	17 Jun, 18:00	78.474	8.343	10.63%	39.751
SB3	17 Jun, 18:00	98.993	11.555	11.67%	48.907
SB4	17 Jun, 18:00	2.238	0.252	11.26%	1.098
SB5	17 Jun, 18:00	108.570	12.346	11.37%	52.841

Across all sub-basins, uncertainty bands remain tightly bound to the peak runoff window on June 17, with the absolute maximum envelope $Q_{\max}$ (blue line) and minimum envelope $Q_{\min}$ (teal line) collapsing back to zero variance within 24 hours (Figure 1a–e). Visually comparing SB3 (Figure 1c) and SB5 (Figure 1e) against the micro-scale catchment SB4 (Figure 1d) confirms that while relative parameter sensitivity creates a uniform proportional spread across all hillslopes $\sim 11\%$, absolute variance is scaled strictly by catchment size.

The downstream routing transformation is clear at the basin outlet (Figure 1f). Unlike the sharply pointed upstream curves, the Sink-1 hydrograph displays a flattened crest due to a 6-hour translation lag. The visual clustering of the standard deviation boundaries around the mean flow in Figure 1f demonstrates the downstream reduction in relative uncertainty down to an efficient 4.32%.

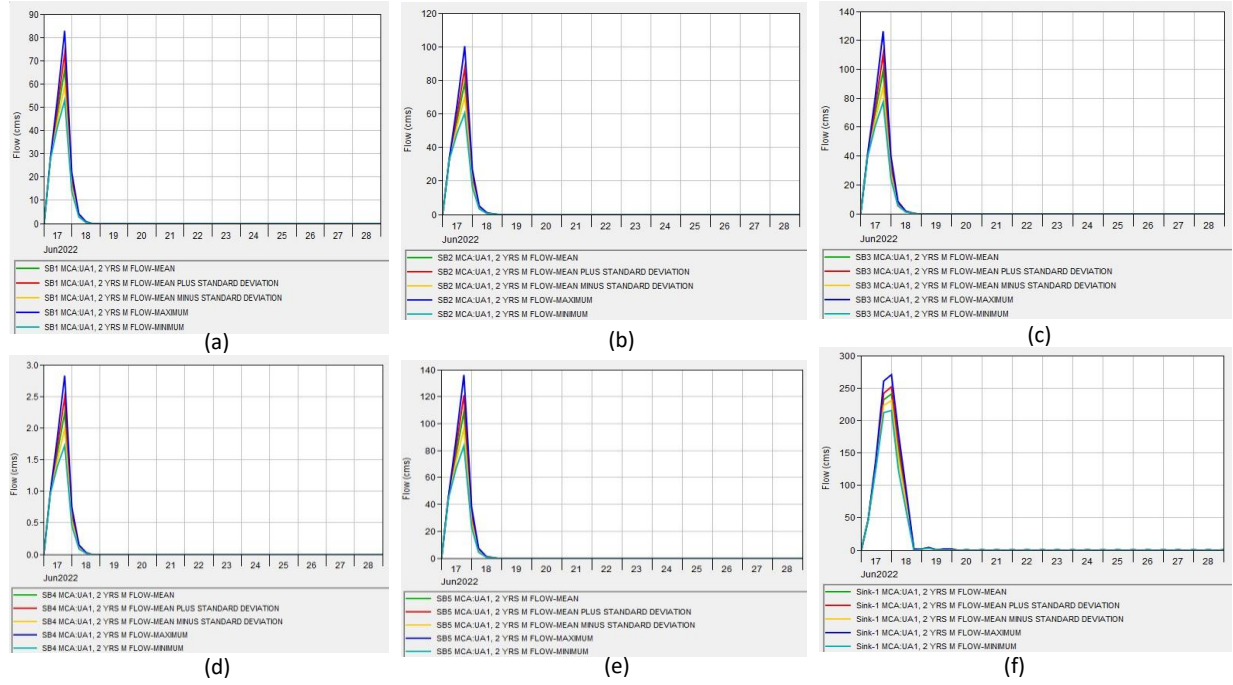


Figure 1. Stochastic ensemble hydrographs for the high-frequency $T = 2$ -year recurrence interval event $AEP = 50.0\%$ across the constituent sub-basins and primary catchment outlet: (a) SB1, (b) SB2, (c) SB3, (d) SB4, (e) SB5, and (f) Sink-1. The solid lines track the temporal progression of the ensemble mean discharge (μ , green), the standard deviation variance bounds ($\mu \pm \sigma$, red and orange), and the absolute boundary envelopes $Q_{\max}$ and $Q_{\min}$ (blue and teal) generated via Monte Carlo sampling

3.1.2. The Medium-Magnitude 10-Year Recurrence Boundary

The structural changes in the catchment's response under medium-magnitude forcing are compiled across all sub-basins in **Table 2** and tracked in **Figure 2**.

Table 2: Sub-Basin Peak Flow Uncertainty and Envelopes (10-Year Event)

Location	Peak Time	Mean Flow μ (m3/s)	Std Dev σ (m3/s)	Relative Uncertainty (%)	Absolute Spread ($Q_{\max} - Q_{\min}$, m3/s)
SB1	17 Jun, 18:00	132.690	17.500	13.19%	74.990
SB2	17 Jun, 18:00	156.240	20.970	13.42%	99.790
SB3	17 Jun, 18:00	197.010	29.100	14.77%	123.170

SB4	17 Jun, 18:00	4.441	0.634	14.28%	2.761
SB5	17 Jun, 18:00	216.940	31.030	14.30%	132.700

Unlike the single-peak 2-year baseline, the 10-year sub-basin curves (Figure 2a–e) show a distinct secondary runoff pulse between June 25 and June 28. The widening gap between the upper and lower standard deviation limits near the primary crests on June 17 visually demonstrates an upward shift in relative uncertainty 13.19% – 14.77% , highlighting the model's increased sensitivity to loss parameters as the soil profile reaches high saturation levels.

Downstream variance propagation is captured at the basin outlet in **Figure 2f**. The routing network's relative smoothing effect is clear, as the standard deviation lines cluster more tightly around the mean flow than in the upstream panels. However, the absolute envelope maximum $Q_{\max}$, blue line) reaches a prominent peak of 683.13 m³/s The secondary peak on June 26 matches a substantial widening of the absolute envelope spread $Q_{\max} - Q_{\min}$, proving that absolute uncertainty remains highly significant throughout the entire duration of the flood wave.

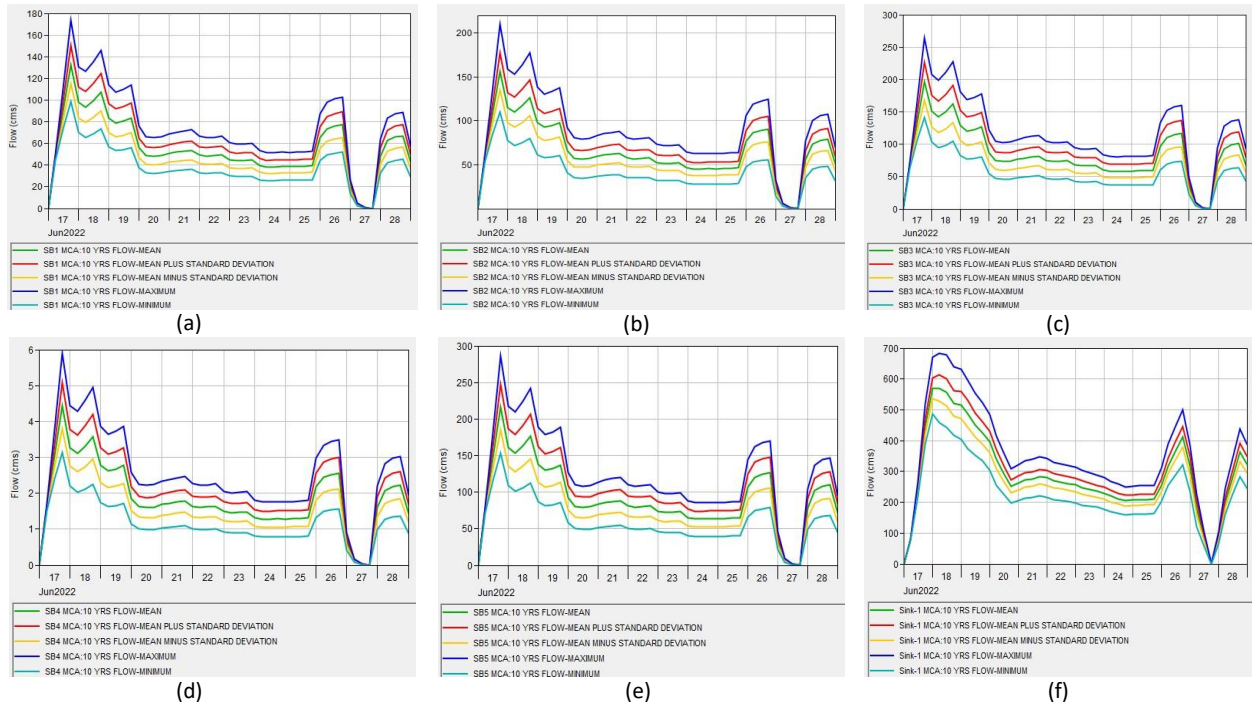


Figure 2. Stochastic ensemble hydrographs for the medium-magnitude $T = 10$ -year recurrence interval event $AEP = 10.0\%$ across the constituent sub-basins and primary catchment outlet: (a) SB1, (b) SB2,

(c) SB3, (d) SB4, (e) SB5, and (f) Sink-1. The curves map the temporal progression of the ensemble mean discharge μ (green), the standard deviation variance bounds $\pm\sigma$ (red and orange), and the absolute boundary envelopes ($Q_{\max}$ and $Q_{\min}$, blue and teal). The structural appearance of the secondary discharge pulse between June 25 and June 28 highlights the onset of an extended, volume-driven catchment drainage profile.

3.1.3. The Extreme 50-Year Recurrence Boundary

The extreme multi-day configuration of the 50-year hydrologic response is compiled across all sub-basins in **Table 3** and mapped across the ensemble paths of **Figure 3**.

Table 3: Sub-Basin Peak Flow Uncertainty and Envelopes (50-Year Event)

Location	Peak Time	Mean Flow μ (m ³ /s)	Std Dev σ (m ³ /s)	Relative Uncertainty (%)	Absolute Spread ($Q_{\max}$ – $Q_{\min}$, m ³ /s)
SB1	17 Jun, 18:00	206.760	29.830	14.43%	127.700
SB2	17 Jun, 18:00	243.080	35.780	14.72%	170.150
SB3	17 Jun, 18:00	306.430	49.680	16.21%	210.210
SB4	17 Jun, 18:00	6.898	1.083	15.70%	4.717
SB5	17 Jun, 18:00	338.050	52.930	15.66%	226.230

Under this intensified storm, the primary runoff peak on June 17 transitions into an extended flow plateau that remains elevated for over a week before entering a multi-stage recession. As seen in the macro-scale sub-basins SB3 (**Figure 3c**) and SB5 (**Figure 3e**), the gap between the upper and lower standard deviation lines $\mu \pm \sigma$ expands significantly at the primary peaks. This pattern visually demonstrates that under extreme storms, the model's sensitivity approaches an asymptotic ceiling as the watershed reaches full soil profile saturation.

The catchment's regime shift is captured at the basin outlet in **Figure 3f**. While individual sub-basins reach their maximum values during the initial surge on June 17, the downstream outlet hydrograph displays a distinct structural translocation. Routing network and channel storage delay peak translation, causing the initial surge on June 18 to level off. Crucially, the delayed accumulation of multi-day water volumes triggers an intense secondary peak on June 26,

establishing the absolute maximum mean discharge $907.91 \text{ m}^3/\text{s}$. The widening of the absolute envelope maximum $Q_{\max}$ up to $1087.50 \text{ m}^3/\text{s}$ during this late-event pulse underscores that under extreme return periods, basin memory and delayed synchronization dictate the worst-case design flood boundaries.

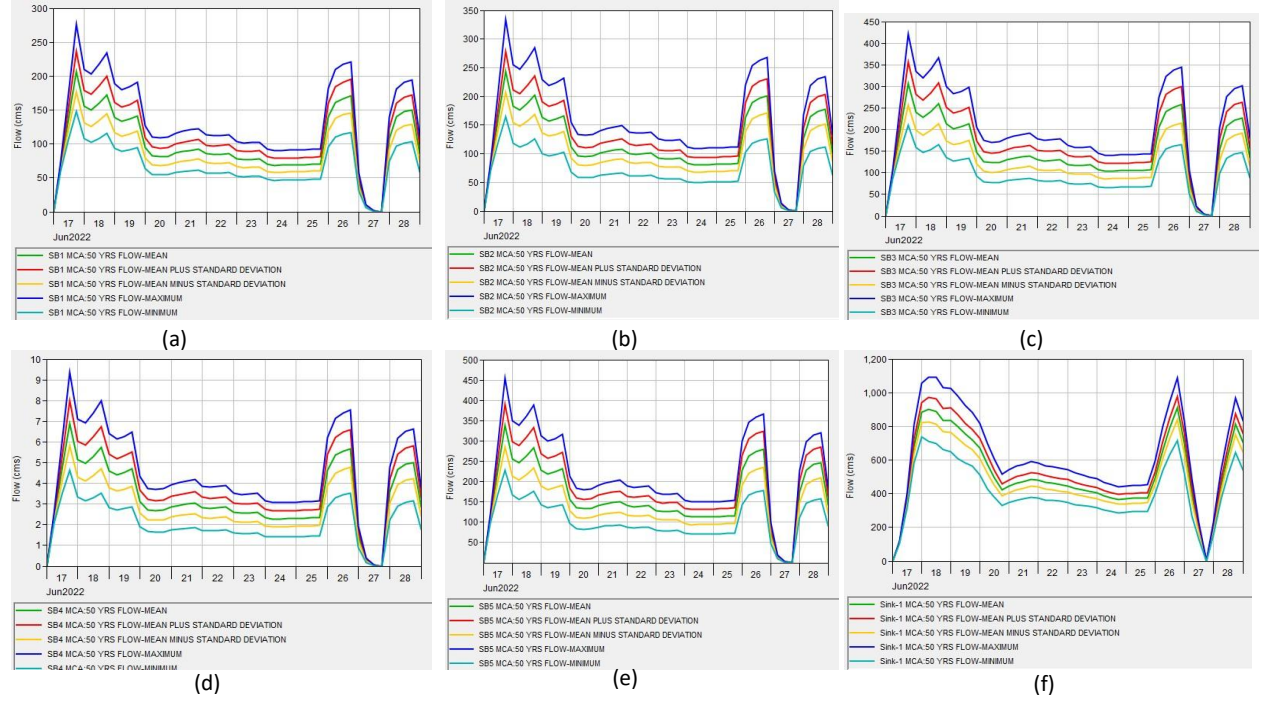


Figure 3. Stochastic ensemble hydrographs for the extreme $T = 50$ -year recurrence interval event $AEP = 2.0\%$ across the constituent sub-basins and primary catchment outlet: (a) SB1, (b) SB2, (c) SB3, (d) SB4, (e) SB5, and (f) Sink-1. The panels illustrate a systemic hydrologic regime shift at the basin outlet (Sink-1), where delayed channel-floodplain routing and upstream wave accumulation translocate the absolute design flood peak from the initial runoff surge to a delayed, late-event pulse on June 26 at 18:00, expanding the absolute maximum envelope boundary $Q_{\max}$ up to $1087.50 \text{ m}^3/\text{s}$.

3.1.4. The Century-Scale 100-Year Recurrence Boundary

The extreme volume-driven characteristics of the 100-year event are compiled across all sub-basins in **Table 4** and tracked visually in **Figure 4**.

Table 4: Sub-Basin Peak Flow Uncertainty and Envelopes (100-Year Event)

Location	Peak Time	Mean Flow	Std Dev σ	Relative	Absolute Spread
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		μ (m ³ /s)	(m ³ /s)	Uncertainty (%)	(Q _{max} –Q _{min} , m ³ /s)
SB1	17 Jun, 18:00	242.340	35.810	14.78%	153.250
SB2	17 Jun, 18:00	284.780	42.980	15.09%	204.310
SB3	17 Jun, 18:00	358.960	59.660	16.62%	252.460
SB4	17 Jun, 18:00	8.078	1.302	16.12%	5.668
SB5	17 Jun, 18:00	396.210	63.560	16.04%	271.620

The initial flood crest on June 17 transitions into a prolonged plateau of high runoff before reaching a distinct secondary pulse between June 25 and June 28 (**Figure 4a–e**). As seen in the macro-scale sub-basins SB3 (**Figure 4c**) and SB5 (**Figure 4e**), the gap between the upper and lower standard deviation lines expands significantly at the primary peaks. This pattern visually demonstrates that under century-scale storms, the model's sensitivity approaches an asymptotic maximum as the watershed reaches full soil profile saturation.

The multi-peak non-stationarity of the uncertainty propagation is clearly illustrated at the basin outlet in **Figure 4f**. Unlike the upstream sub-basins where the initial surge dominates, the Sink-1 hydrograph displays a complete shift in peak dominance. The routing network's structural capacity to damp relative variance is clear from the stable~ 7.48%relative band gap. However, the absolute envelope maximum ($Q_{\max}$ blue line) peaks intensely during the second pulse on June 26, reaching an extraordinary value of 1354.30 m³/s. This visual widening of the total boundary gap ($Q_{\max} - Q_{\min}$) during the late-event crest underscores the absolute scale problem, demonstrating that delayed wave superposition and network accumulation govern the worst-case flood boundaries.

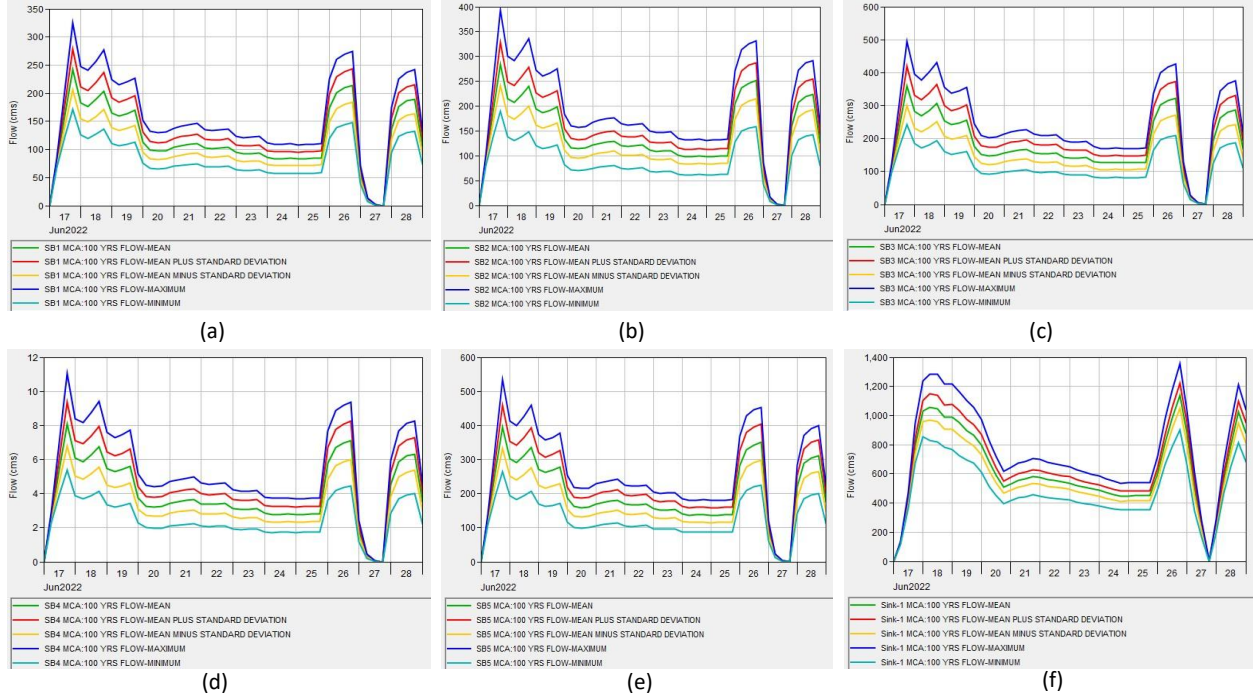


Figure 4. Stochastic ensemble hydrographs for the century-scale $T = 100$ -year recurrence interval event $AEP = 1.0\%$ across the constituent sub-basins and primary catchment outlet: (a) SB1, (b) SB2, (c) SB3, (d) SB4, (e) SB5, and (f) Sink-1. The widening gap between the standard deviation lines at the upstream peaks highlights asymptotic relative parameter sensitivity under full catchment saturation conditions, while the visible widening of the absolute flow envelope $Q_{\max} - Q_{\min}$ to a massive spread of $451.60 \text{ m}^3/\text{s}$ at the late-event outlet crest underscores the absolute scaling problem.

3.1.5. The Upper-Bound 200-Year Recurrence Boundary

The upper-bound envelope metrics representing maximum possible variance propagation across all sub-basins are compiled in **Table 5** and visually synthesized in **Figure 5**.

Table 5: Sub-Basin Peak Flow Uncertainty and Envelopes (200-Year Event)

Location	Peak Time	Mean Flow μ (m ³ /s)	Std Dev σ (m ³ /s)	Relative Uncertainty (%)	Absolute Spread ($Q_{\max} - Q_{\min}$, m ³ /s)
SB1	17 Jun, 18:00	280.340	42.200	15.05%	180.550
SB2	17 Jun, 18:00	329.300	50.680	15.39%	240.830
SB3	17 Jun, 18:00	415.050	70.340	16.95%	297.640
SB4	17 Jun, 18:00	9.337	1.535	16.44%	6.686

SB5	17 Jun, 18:00	458.320	74.930	16.35%	320.150
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The initial peak on June 17 transitions into a highly stable, multi-day high-flow plateau, followed by a sharp secondary runoff crest between June 25 and June 28 (**Figure 5a–e**). Visually tracking the standard deviation envelope $\mu \pm \sigma$ across the macro-catchments SB3 (**Figure 5c**) and SB5 (**Figure 5e**) reveals that the proportional band width stabilizes almost identically to the 100-year event layout, confirming that relative parameter sensitivity has reached an asymptotic saturation threshold $\sim 16.5\%$. However, due to the massive volume of extreme precipitation, the absolute maximum envelope $Q_{\max}$ (blue line) scales up severely, reaching peak values of $575.62 \text{ m}^3/\text{s}$ (SB3) and $622.11 \text{ m}^3/\text{s}$.

The cumulative effect of this extreme parameter variance under network routing interactions is visually summarized at the basin outlet in **Figure 5f**. While the standard deviation boundaries cluster tightly around the mean—confirming that the relative variance smoothing mechanism holds steady at its structural threshold of $\sim 7.26\%$ —the absolute envelope margins display extraordinary expansion. The absolute maximum envelope $Q_{\max}$ (blue line) peaks intensely during the translocated second pulse on June 26, surging to a critical maximum of $1646.10 \text{ m}^3/\text{s}$. This visual gap represents a massive maximum-to-minimum envelope spread of $536.20 \text{ m}^3/\text{s}$ clearly demonstrating that relying on single deterministic hydrographs is highly vulnerable for downstream hydraulic freeboard or flood protection design.

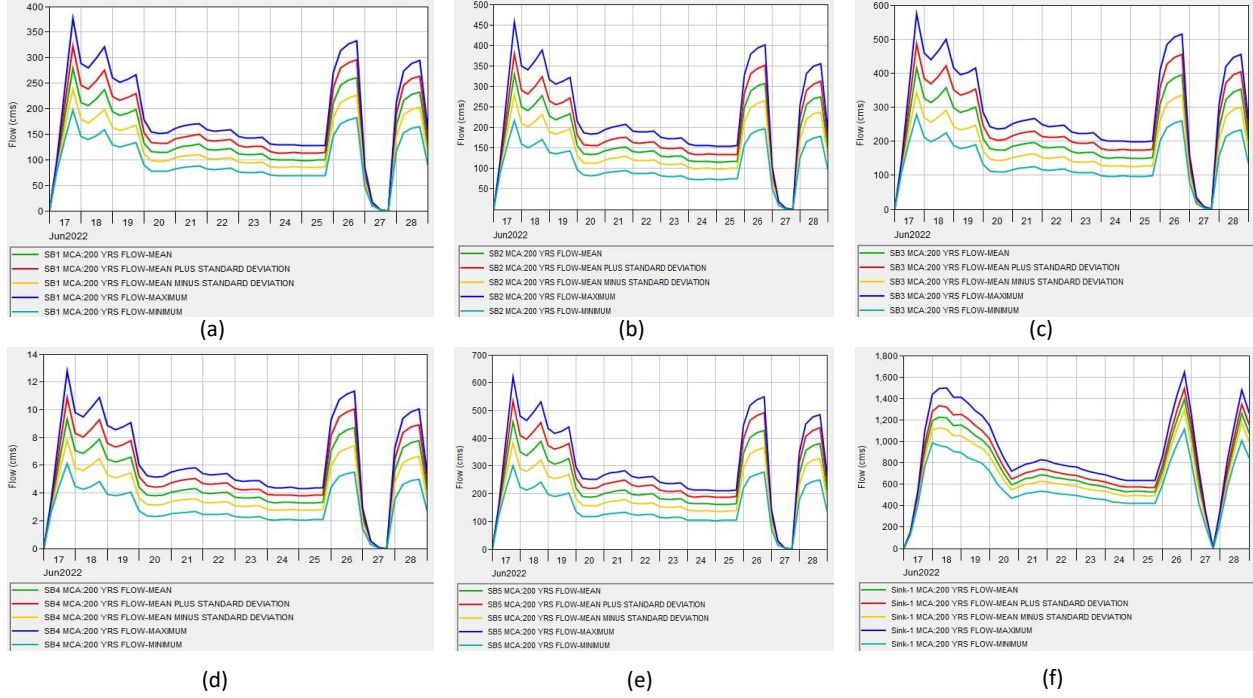


Figure 5. Stochastic ensemble hydrographs for the extreme upper-bound $T = 200$ -year recurrence interval event $AEP = 0.5\%$ across the constituent sub-basins and primary catchment outlet: (a) SB1, (b) SB2, (c) SB3, (d) SB4, (e) SB5, and (f) Sink-1. The visual layout summarizes maximum variance propagation across the modeling chain, establishing that while the channel routing network maintains a stable relative uncertainty threshold of $\sim 7.26\%$ downstream, the absolute envelope spread expands to a critical maximum of $536.20 \text{ m}^3/\text{s}$ at the final flood crest, creating a high-impact boundary condition vector for subsequent hydraulic routing.

3.2. Cross-Event Synthesis & Key Structural Takeaways

To contextualize the non-linear transformation of the extreme design floods across all evaluated recurring intervals, a comprehensive cross-event synthesis database is established in **Table 6**.

The uncertainty analysis indicates that peak discharge at the basin outlet increases substantially with return period, rising from $241.16 \text{ m}^3/\text{s}$ for the 2-year event to $1391.10 \text{ m}^3/\text{s}$ for the 200-year event. Although the relative outlet uncertainty remains moderate ($4.32\text{--}7.71\%$), the absolute spread between maximum and minimum peak discharges increases markedly from $54.46 \text{ m}^3/\text{s}$ to $536.20 \text{ m}^3/\text{s}$, reflecting greater uncertainty in extreme flood estimates.

A similar trend is observed across the sub-basins, where relative uncertainty increases from $10.49\text{--}11.67\%$ to $15.05\text{--}16.95\%$ with increasing return period. The dominant hydrological

controls also shift from infiltration-excess runoff during frequent events to channel routing, basin storage effects, multi-peak superposition, and parameter saturation during extreme events. These results suggest that hydrological uncertainty and process complexity increase as flood magnitude becomes larger.

Table 6: Cross-Frequency Analytical Synthesis of Flood Output and Structural Uncertainty Boundaries at Sink-1

Return Period (T)	Outlet Peak Mean μ (m ³ /s)	Outlet Peak Time	Sub-Basins Relative Uncertainty Range	Outlet Relative Uncertainty	Outlet Absolute Spread (Q _{max} – Q _{min})	Dominant Hydrologic Driver
2-Year	241.16	June 17, 24:00	10.49% – 11.67%	4.32%	54.46 m ³ /s	Flashy, Infiltration-Excess Runoff
10-Year	570.24	June 18, 06:00	13.19% – 14.77%	7.57%	223.58 m ³ /s	Channel Routing & Flow Translation
50-Year	907.91	June 26, 18:00	14.43% – 16.21%	7.71%	370.91 m ³ /s	Basin Memory & Pulse Translocation
100-Year	1137.70	June 26, 18:00	14.78% – 16.62%	7.48%	451.60 m ³ /s	Multi-Peak Superposition
200-Year	1391.10	June 26, 18:00	15.05% – 16.95%	7.26%	536.20 m ³ /s	Asymptotic Parameter Saturation

3.3. Empirical Flood Frequency Analysis at Catchment Outlet

Stochastic flood frequency analysis (FFA) was performed at the primary basin outlet (**Sink-1**) to project design flood hydrographs across multiple return periods. The calculated peak discharges corresponding to distinct Annual Exceedance Probabilities (AEP) are structured in **Table 7**.

Table 7: Deterministic Peak Discharge and Annual Exceedance Probability (AEP) at Sink-1

Return Period (T, years)	Annual Exceedance Probability (AEP, %)	Peak Discharge (Qp, m3/s)
2	50.0%	1604.2
10	10.0%	3107.8
50	2.0%	4479.3
100	1.0%	5070.8
200	0.5%	5707.9

The empirical frequency distribution showcases an intense, non-linear growth trajectory. The 200-year extreme design flood 5707.9 m³/s scales by a factor of 3.55 relative to the high-frequency 2-year baseline event 1604.2 m³/s.

When plotted on a semi-logarithmic scale (**Figure 6**), the frequency curve displays an upward steepening trend toward the higher-order recurrence intervals $T \geq 50$ years. This trend reflects a classic threshold-crossing mechanism typical of steep, mountainous catchments. In these flashy hydrological systems, once intense multi-day design storms satisfy initial soil moisture abstractions, the drainage network transitions rapidly into a fully saturated state. With no remaining basin storage capacity, minor step-increases in precipitation intensity cause disproportionately massive surges in peak discharge at the outlet.

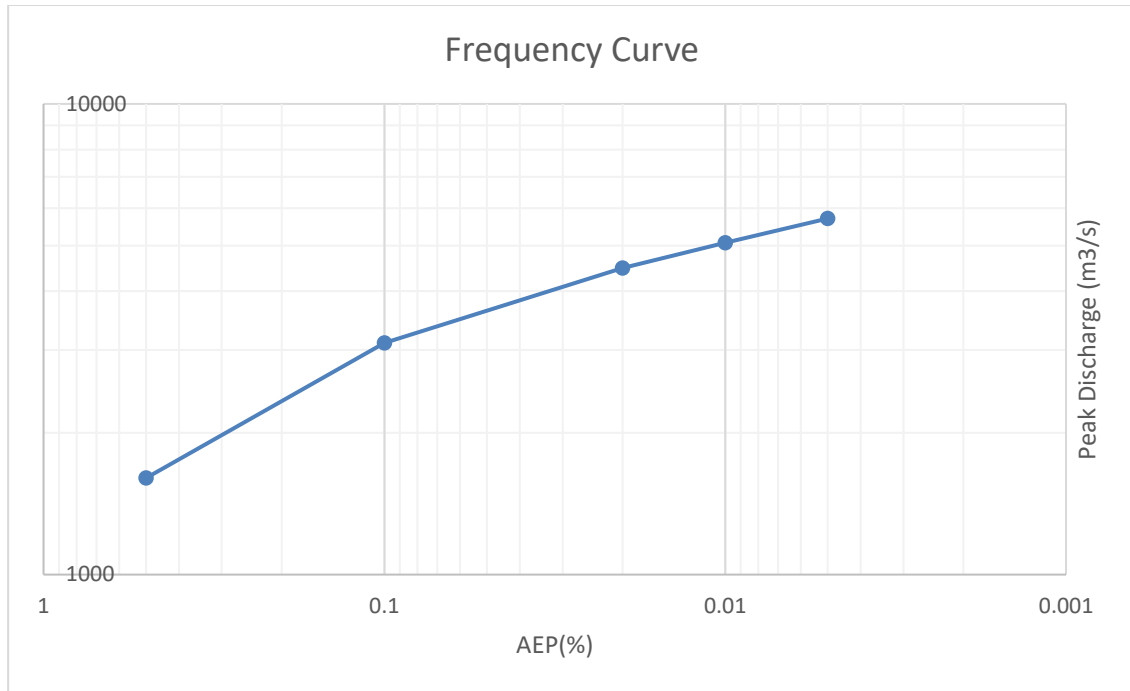


Figure 6 Flood frequency curve showing the relationship between annual exceedance and Peak Value

3.4. Spatial Disaggregation of Sub-Basin Runoff Generation

To isolate the regional source zones driving flood generation, runoff accumulation was disaggregated at the individual sub-basin scale across all target frequencies **Table 8**.

Table 8: Sub-Basin Area and Spatial Peak Discharge Scaling Vector

Hydrologic Element	Area (km2)	Qp 2-yr (m3/s)	Qp 10-yr (m3/s)	Qp 50-yr (m3/s)	Qp 100-yr (m3/s)	Qp 200-yr (m3/s)
SB1	633.5	383.1	745.7	1078.9	1221.7	1365.1
SB2	758.9	458.3	892.3	1291.2	1462.2	1634.0
SB3	969.2	568.6	1113.3	1615.9	1831.7	2048.5
SB4	21.9	13.2	25.8	37.3	42.2	47.2
SB5	1037.4	623.2	1214.5	1758.6	1991.8	2226.1

The spatial decomposition confirms that absolute peak flows are governed by sub-basin drainage area rather than localized micro-topographic slopes. The macro-scale units SB51037.4 km² and **SB3** 969.2 km² consistently generate the largest runoff volumes, discharging peak flows of 2226.1 m³/s and 2048.5 m³/s respectively, at the 200-year boundary.

Conversely, the micro-scale catchment SB421.9 km² exhibits a highly flashy response with an early time-to-peak, but contributes a negligible volumetric fraction $47.2 \text{ m}^3/\text{sat}T = 200 \text{ years}$. This layout proves that regional flood planning and downstream boundary condition hazards are structurally controlled by the basin's largest geomorphic components.

3.5. Confluence Routing and Hydrograph Synchronization Dynamics

The transformation and movement of the flood wave through channel reaches and major confluences are compiled in **Table 9**. The simulated peak discharges show a consistent increase with return period across all hydrologic elements. At the basin outlet (Sink-1), the peak discharge rises from 1604.2 m³/s for the 2-year event to 5707.9 m³/s for the 200-year event, indicating a substantial increase in flood magnitude under extreme rainfall conditions. Similar trends are observed at the confluence points (J1 and J2) and routed reaches (R1 and R2), reflecting the cumulative contribution of upstream flows and increasing runoff generation.

The results also highlight the influence of channel routing on flood attenuation, as routed reaches generally exhibit slightly lower peak discharges than their corresponding upstream junctions. Overall, the progressive increase in peak discharge with return period demonstrates the growing flood risk and the importance of considering extreme-event scenarios in watershed management and flood mitigation planning.

Table 9: Peak Discharge (Qp) Evolution across Confluences and Routing Channel

Hydrologic Element	Area (km ²)	Qp 2-yr (m ³ /s)	Qp 10-yr (m ³ /s)	Qp 50-yr (m ³ /s)	Qp 100-yr (m ³ /s)	Qp 200-yr (m ³ /s)
J2 (Upper Confluence)	2006.7	1191.9	2327.8	3374.4	3823.5	4274.6
R2 (Routing from J2)	2006.7	1095.4	2120.5	3051.2	3447.7	3843.6

J1 (Main Confluence)	3399.0	1647.5	3138.1	4483.0	5055.0	5652.6
R1 (Routing from J1)	3399.0	1595.5	3091.8	4456.8	5041.9	5675.9
Sink-1 (Outlet)	3420.9	1604.2	3107.8	4479.3	5070.8	5707.9

3.5.1. Time-to-Peak and Flow Synchronization Analysis

A critical finding is the dual role that channel reaches play across different recurrence intervals.

Low-to-Medium Events $T \leq 10$ years): Reach channels introduce typical hydraulic attenuation. For example, routing through **R2** drops the peak by 8.9% during a 10-year event due to channel storage and friction.

Extreme Events $T \geq 100$ years): This attenuation capacity is systematically overwhelmed. Under the 200-year extreme scenario, routing through reach **R1** down to the outlet sees the peak discharge jump from 5652.6 m³/s (**J1**) to 5707.9 m³/s (**Sink-1**).

This amplification stems from **hydrograph synchronization**. Under high-intensity, widespread design storms, sub-basin peaks align closely in time. All sub-basins hit their individual runoff peaks simultaneously on **June 17 at 18:00**. While routing through reach R2 introduces a 12-hour translation lag (shifting the peak to June 18 at 06:00), this delayed wave arrives at the lower main confluence (**J1**) exactly as the slow-responding, large-volume runoff contributions from lower sub-basins converge. This synchronization creates a compounding effect, where the delayed upstream flood wave merges with localized runoff peaks. This process counteracts standard channel attenuation and increases peak discharges immediately upstream of the basin outlet.

3.6. Volumetric Mass Balance Verification

While peak discharge Q_p fluctuates based on network routing and hydrograph synchronization, the normalized volumetric runoff depth (mm) remains uniform across the sub-basins for any given recurrence interval. This uniformity confirms that the meteorological design storm is the primary driver of the overall water balance. The internal basin parameters—such as the SCS Curve Number (CN) and terrain slope—do not alter the total mass of water generated. Instead,

they dictate the hydrograph's shape, time-to-peak (T_p), and steepness. This confirms the internal consistency of the HEC-HMS model and verifies that the mass-balance framework is robust enough to provide reliable boundary conditions for subsequent unsteady flow routing in HEC-RAS.

4. Conclusions

This study established a coupled multi-frequency flood frequency analysis (FFA) and a generalized stochastic parameter uncertainty framework within a complex, flashy watershed (3420.9 km^2). By tracking five core statistical descriptors across multiple recurrence intervals $T = 2$ to 200 years the investigation revealed the non-linear mechanics that govern wave translation, parameter sensitivity, and variance propagation. The major findings are as follows:

1. Spatial uncertainty analysis identified SB5 (30.3%) and SB3 (28.3%) as the major contributors to runoff generation and absolute predictive uncertainty, although relative parameter sensitivity remained nearly uniform ($\approx 11\text{--}17\%$) across all sub-basins.
2. Flood response exhibited a non-linear transition with increasing return period. For events ≤ 10 years, the initial runoff peak dominated downstream flow, whereas for events ≥ 50 years, delayed basin storage generated a larger secondary peak, reaching $1391.10 \text{ m}^3/\text{s}$ for the 200-year event.
3. Parameter uncertainty increased from approximately 11% for the 2-year event and approached an asymptotic limit of 15–17% under extreme events, indicating saturation of loss-parameter sensitivity after complete catchment wetting.
4. Channel routing reduced relative uncertainty at the watershed outlet, maintaining a stable value of approximately 7.5% despite increasing upstream variability, demonstrating the smoothing effect of flow aggregation.
5. Despite this stable relative uncertainty, the absolute discharge envelope expanded substantially from $54.46 \text{ m}^3/\text{s}$ (2-year event) to $536.20 \text{ m}^3/\text{s}$ (200-year event), highlighting the increasing engineering significance of uncertainty for extreme floods.
6. These findings demonstrate that deterministic design hydrographs alone may underestimate hydraulic risk. Incorporating uncertainty bounds into downstream hydraulic models such as HEC-RAS can improve the reliability of flood inundation mapping and infrastructure design under extreme flood conditions.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

All authors contributed to the conceptualization and design of the study. The authors contributed to data collection, methodology, analysis, modelling, interpretation of results, and preparation and revision of the manuscript. All authors read and approved the final manuscript.

Data Availability Statement

Some data used during this study were provided by third-party agencies, including the India Meteorological Department (IMD), the Central Water Commission (CWC), and publicly available geospatial databases. The processed datasets, calibrated model files, and other materials supporting the findings of this study are available from the corresponding author upon reasonable request.

Data Availability Statement

- a. Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.
- b. Some or all data, models, or code used during the study were provided by a third party. Direct requests for these materials may be made to the provider, India Meteorological Department (IMD)

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