A Project Report

On

Flood Frequency Analysis Using Statistical Methods

BY

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ABSTRACT

Flood frequency analysis (FFA) is a critical hydrological tool for estimating flood recurrence intervals and guiding hydraulic structure design. This study expands on traditional methods by evaluating Gumbel Extreme Value, Log-Pearson Type III (LP3), Log-Normal, Weibull, and Gamma distributions, validated through Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests and performance metrics - Root Mean Squared Error (RMSE), Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE). Implemented in R with an interactive Shiny web application, the analysis uses discharge data from the Nizam Sagar reservoir (2015–2024) as a proxy for river discharge due to limited Central Water Commission (CWC) data. The 10-year dataset introduced uncertainty in long-term predictions, particularly for return periods >50 years. These insights aid flood mitigation planning while highlighting the need for extended hydrological records to improve extreme event modelling.

CONTENTS

INTRODUCTION

Floods pose significant risks to infrastructure, the environment, and human settlements, making accurate predictions essential for mitigation and management. Flood frequency analysis enables engineers and policymakers to estimate the probability of flood occurrences for a given return period, informing design standards and land-use planning.

Traditional statistical approaches are widely used for estimating extreme flood events. This study expands beyond the previously analysed Gumbel Extreme Value (EV) and Log-Pearson Type III (LP3) distributions to include Log-Normal, Gamma, and Weibull distributions. Each distribution offers unique characteristics that may better capture the behaviour of flood data in different hydrological contexts:

- The **Gumbel EV distribution** provides a straightforward method for initial flood assessment with relative simplicity.
- The **LP3 distribution** accounts for skewness often present in hydrological data, offering a more nuanced representation of flood events in regions with significant variability.
- The **Log-Normal distribution** is useful when data exhibits a logarithmic relationship and has been widely applied in hydrological studies.
- The **Gamma distribution** provides flexibility for modelling skewed data with positive values, which is common in flood analysis.
- The **Weibull distribution** is particularly suitable for analysing extreme events and has applications in reliability analysis.

This comprehensive study applies these methods to discharge data from the Nizam Sagar reservoir (2015–2024) and incorporates rigorous statistical testing through Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) goodness-of-fit tests, alongside performance metrics (RMSE, Nash-Sutcliffe, Kling-Gupta) to evaluate distribution suitability. To enhance accessibility and reproducibility, an interactive Shiny web application was developed in R, enabling dynamic visualisation of fitted distributions, return period estimates, and statistical results in real-time.

By integrating advanced statistical methods, robust validation frameworks, and modern computational tools, this analysis aims to improve on traditional FFA approaches.

METHODOLOGY

Data Preparation

1. Data Source: Daily discharge records (2015-2024) have been obtained from the Nizam Sagar reservoir. These data represent relative daily inflow volumes rather than direct river discharge measurements.

2. Annual Maximum Series (AMS):

- Annual Maximum Series (AMS) are created using yearly peak discharges from the raw data.
- Missing values are removed to ensure the integrity of the dataset.
- Data was processed using R packages, including *readxl* for importing Excel files and *lubridate* for datetime manipulation.

3. Weibull Formula:

AMS data is ranked in descending order, and probabilities are calculated using the Weibull formula:

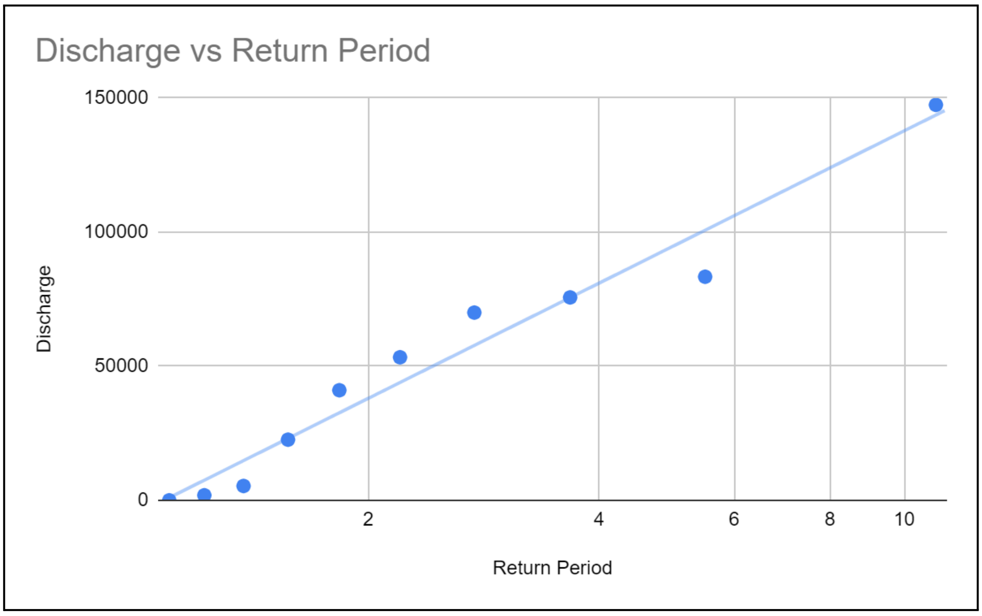
$$P = \frac{m}{n+1}$$

where m is the rank of the data point and n is the total number of data points.

Return Periods(T) are then derived using

$$T = \frac{1}{P}$$

year	ams	Rank	WeibullProb	ReturnPeriod
2016	147448	1	0.1	10
2020	83359	2	0.2	5
2021	75654	3	0.3	3.33333333333333
2022	70000	4	0.4	2.5
2024	53335	5	0.5	2
2023	41044	6	0.6	1.66666666666667
2017	22612	7	0.7	1.428571428571429
2019	5350	8	0.8	1.25
2018	1877	9	0.9	1.11111111111111



4. Pre-processing:

- Log transformation was applied to stabilise variance and normalise the data distribution, for use in appropriate distributions
- Statistical parameters (mean, standard deviation, skewness) were calculated for raw and transformed data.

Methodological Context from Literature

The study partially draws upon data characteristics, methodological approaches, and general findings from the Lower Burhi Dehing River (LBDR) (1972-1997), as presented in Handique et al. (2024), the Lower Mahi River (1980-2009) as described in Bhagat (2017) and the Jiadhal River Basin (1973 - 2018) as described in Gogoi & Patnaik (2023) to understand the applicability of different methods and the importance of data quality.

Statistical Methods

1. Gumbel EV Distribution

The Gumbel distribution was implemented using both the Method of Moments Estimation (MME) and the Maximum Likelihood Estimation (MLE) approaches:

- **MME Implementation**:
  - Reduced Variate (Y): Reduced variates have been derived using Excel calculations with the standard formulas associated with the Gumbel distribution.

$$Y_T = -\ln\left(-\ln\left(\frac{T}{T-1}\right)\right)$$

  - Frequency factor (K) was computed using $K = \frac{Y_T - Y_N}{S_N}$ where Y_N and S_N are the reduced mean and standard deviation, respectively, which are dependent on the sample size.
  - Discharge estimation: $Q_T = \overline{X} + K.\sigma$, Where Q_T is the estimated discharge for the return period T , $\overline{X}$ is the mean of the annual maximum discharge series, and σ is the sample standard deviation of the annual maximum discharge series.
- **MLE Implementation**:
  - The *extRemes* package in R was used to fit the Gumbel distribution (*shape = 0* in GEV)
  - Parameters were estimated using the *fevd()* function
  - Return levels were calculated using the *return.level()* function

2. Log-Pearson Type III Distribution

- Log Transformation: Discharge values are transformed to logarithmic form with base 10 to stabilize variance and normalize the data distribution.
- Formula: The Log-Pearson Type III distribution uses the following formula:

$$\log(Q_T) = \overline{z} + K_z.\sigma_z$$

where Q_T is the estimated flood discharge for a return period T,

$\overline{z}$ the mean of the log-transformed annual maximum discharge series,
σ_z the sample standard deviation of the log-transformed annual maximum discharge series, and
K_z the frequency factor, dependent on the skewness coefficient and return period.

- Skewness Coefficient

  The coefficient of skewness (C_s) is calculated using the below formula for accurate modelling in hydrological frequency analysis:

$$C_s = \frac{N.\Sigma(z-\bar{z})^3}{(N-1)(N-2)(\sigma_z)^3}$$

  Where N is the number of data points

  z is the log-transformed discharge value

  $\bar{z}$ is the mean of the log-transformed discharge values, and

  σ_z is the sample standard deviation of the log-transformed discharge values.

- The frequency factor K_z is then approximated using the *Wilson-Hilferty approximation*.

3. Log-Normal distribution:

The Log-Normal distribution was fitted using both MME and MLE approaches:

- **MME Implementation**:
  - Log-transformation was applied to the data
  - Mean and standard deviation of log-transformed data were calculated
  - Z-scores were determined for given return periods
  - Discharge values were estimated using: $log(Q_T) = \bar{z} + z \cdot \sigma_z$
- **MLE Implementation**:
  - The *fitdistrplus* package in R was used to fit the log-normal distribution
  - Parameters were estimated using the *fitdist()* function with "lnorm" distribution
  - Discharges were calculated using the *qlnorm()* function

4. Gamma distribution:

The Gamma distribution was implemented using MLE:

- The *fitdistrplus* package was used to fit the Gamma distribution
- Shape and rate parameters were estimated
- Discharge values for various return periods were calculated using the *qgamma()* function

5. Weibull distribution:

The Weibull distribution was implemented using MLE:

- The *fitdistrplus* package was used to fit the Weibull distribution
- Shape and scale parameters were estimated
- Discharge values were calculated using the *qweibull()* function

Note on Estimation Methods: MLE vs. MME:

Maximum Likelihood Estimation (MLE) and Method of Moments Estimation (MME) are two widely used techniques for parameter estimation in statistical distributions:

- **MLE (Maximum Likelihood Estimation):**
  Estimates parameters by maximising the likelihood function so that the observed data is most probable under the assumed distribution. It is generally more accurate, especially with large samples, and is used for Gamma, Weibull, Gumbel, and Log-Normal distributions in this study.

- **MME (Method of Moments Estimation):**
  Estimates parameters by equating the distribution's theoretical moments (like mean, variance) to the sample moments. It is simpler and easier to compute, but may be less accurate for small or skewed samples. MME was used for Log-Pearson Type III and tested for Gumbel and Log-Normal distributions.

Goodness Of Fit Tests

To evaluate the suitability of different distributions, two goodness-of-fit tests were implemented:

1. Kolmogorov-Smirnov (KS) Test

The KS test measures the maximum distance between the empirical and theoretical cumulative distribution functions:

- The *ks.test()* function from base R was used
- The test compares the maximum difference between observed and predicted cumulative probabilities
- Lower KS statistic and higher p-values indicate better fit.

2. Anderson-Darling (AD) Test

The AD test gives more weight to the tails of the distribution, making it particularly suitable for flood frequency analysis:

- The *ad.test()* function from the *goftest* package was used
- The test is more sensitive to deviations in the distribution tails
- Lower AD statistic and higher p-values indicate better fit

Performance Metrics

Three performance metrics were implemented to assess prediction accuracy:

1. Root Mean Square Error (RMSE)

RMSE measures the average magnitude of errors between observed and predicted values:

- Calculated using: $RMSE = \sqrt{(mean((observed - predicted)^2))}$
- Lower values indicate better prediction accuracy

2. Nash-Sutcliffe Efficiency (NSE)

NSE indicates how well the predicted values match the observed data:

- Calculated using: $NSE = 1 - (\Sigma(observed - predicted)^2)/(\Sigma(observed - mean(observed))^2)$
- Values range from $-\infty$ to 1, with 1 indicating perfect prediction
- Values above 0 indicate the model performs better than using the mean as a predictor

3. Kling-Gupta Efficiency (KGE)

KGE provides a comprehensive measure by combining correlation, bias, and variability:

- Calculated using: $KGE = 1 - \sqrt{((r-1)^2 + (\alpha-1)^2 + (\beta-1)^2)}$
  where r is correlation coefficient, α is the ratio of standard deviations, and β is ratio of means
- Values closer to 1 indicate better model performance

Tools

For the mid-semester report, Python3 and its libraries such as Pandas, Numpy and SciPy had been used for data preprocessing. Google Sheets and LibreOffice Calc were used to conduct computations for both the Gumbel and Log-Pearson Type III distributions.

All statistical methods, goodness-of-fit tests, and performance metrics were implemented in R, providing a robust and reproducible analysis workflow. The R implementation offers several advantages over the spreadsheet-based approach used in the mid-semester report in the form of accuracy, reproducibility and efficiency.

To make our analysis more accessible and interactive, we developed a Shiny web application that allows users to:

1. Upload their own flood data in Excel format
2. Run the analysis with multiple distributions
3. View results in interactive tables
4. Compare goodness-of-fit and performance metrics across distributions
5. Download analysis results for further use

The application is hosted online at https://meghr.shinyapps.io/HydrologyFFA/.

The project utilized several specialized R packages to implement the statistical methods, data manipulation, and visualization components. These packages provided essential functionality for the comprehensive analysis:

Data Handling and Manipulation

- ***readxl***: Used to import Excel files containing the Nizam Sagar reservoir discharge data into R. This package efficiently handles various Excel file formats and allows for selective sheet and range reading.

- ***lubridate***: Employed for manipulation and parsing of datetime data, particularly for extracting year information from dates and handling time-series aspects of the hydrological data.

- ***dplyr:*** Utilised for efficient data manipulation and transformation, including filtering, grouping, and summarising operations on the discharge data. This package was essential for creating the Annual Maximum Series (AMS) from the raw inflow data.

Statistical Analysis and Distribution Fitting

- ***extRemes:*** Applied for extreme value analysis, specifically for fitting the Gumbel distribution. This package implements Maximum Likelihood Estimation (MLE) for the Generalized Extreme Value distribution with shape parameter set to zero for Gumbel distribution.

- ***fitdistrplus:*** Used for fitting probability distributions (Log-Normal, Gamma, Weibull) to data using maximum likelihood and other methods. This package provides comprehensive tools for distribution fitting and parameter estimation.

- ***MASS:*** Provided functions for statistical methods and distributions, supporting various aspects of the statistical analysis.

- ***evd:*** Employed for modeling extreme value distributions, complementing the functionality of extRemes for flood frequency analysis.

- ***goftest:*** Used for performing goodness-of-fit tests, particularly the Anderson-Darling test, to evaluate the suitability of different distributions for the discharge data.

Visualization and Interactive Application

- ***shiny:*** Implemented for building the interactive web application that allows users to explore the flood frequency analysis results dynamically. This package enables the creation of reactive, browser-based applications directly from R1.

- ***DT:*** Used for rendering interactive data tables within the Shiny application, facilitating the presentation of return period estimates and goodness-of-fit statistics in an accessible format.

RESULTS

The spreadsheet calculations for both Gumbel and Log-Pearson Type III distributions provided flood discharge magnitude estimates for different return periods for the Nizam Sagar dataset. The results are preliminary due to the limited dataset.

This limitation is reflected in several studies, including those by Bhagat (2017) and Gogoi & Patnaik (2023), who emphasize the necessity of long-term, high-quality discharge data for accurate flood predictions and the appropriate selection of models based on the data.

Spreadsheet-Based Calculations

Gumbel Distribution Results

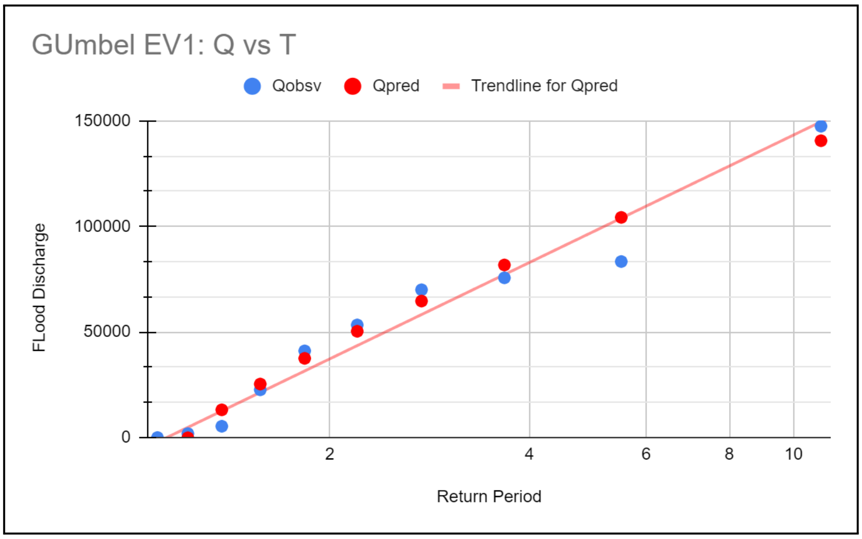
The reduced mean (*Yn*) and the reduced standard deviation (*Sn*) are taken as 0.4952 and 0.9496, respectively, from the Gumbel Distribution tables for a sample size of 10.

T	yT	K	Q
2	0.3665129206	-0.1355171434	43789.44316
5	1.499939987	1.05806654	99087.71355
10	2.250367327	1.848322796	135699.9802
25	3.198534261	2.84681367	181959.6762
50	3.901938658	3.58755124	216277.7613
100	4.600149227	4.322819321	250342.447
200	5.295812143	5.055404531	284282.8365

reduced mean (y	0.4952
reduced std dev	0.9496

T	yT	K	xT
11	2.350618656	1.953894962	140591.0978
5.5	1.606090045	1.169850511	104266.6217
3.666666667	1.144278086	0.6835278915	81735.48282
2.75	0.7941060118	0.314770442	64651.09283
2.2	0.5006512197	0.00574054309	50333.85714
1.833333333	0.2376769509	-0.2711910795	37503.72219
1.571428571	-0.01153413704	-0.5336290407	25345.07295
1.375	-0.2618125616	-0.7971909874	13134.34991
1.222222222	-0.5334173533	-1.083211198	-116.8558
1.1	-0.8745913829	-1.442493032	-16762.2442

Return Period	Qobsv	Qpred
11	147448	140591.0978
5.5	83359	104266.6217
3.666666667	75654	81735.48282
2.75	70000	64651.09283
2.2	53335	50333.85714
1.833333333	41044	37503.72219
1.571428571	22612	25345.07295
1.375	5350	13134.34991
1.222222222	1877	-116.8558
1.1	0	-16762.2442

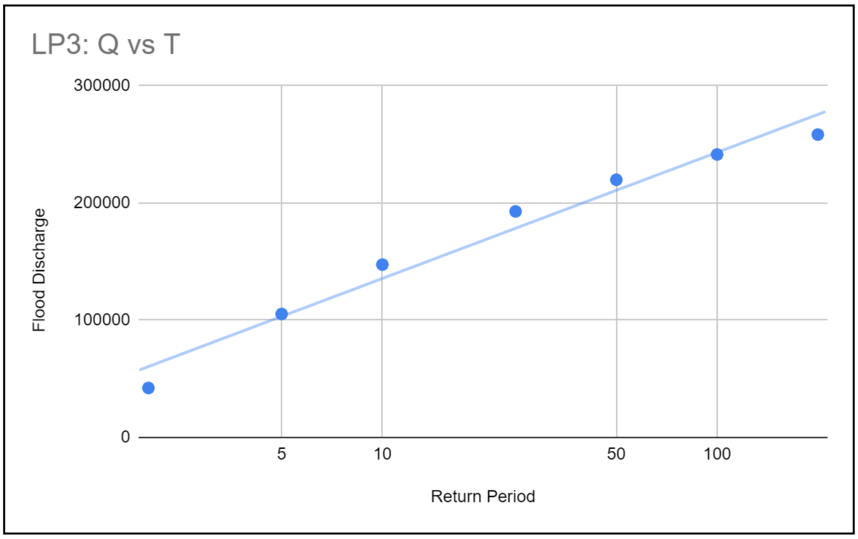


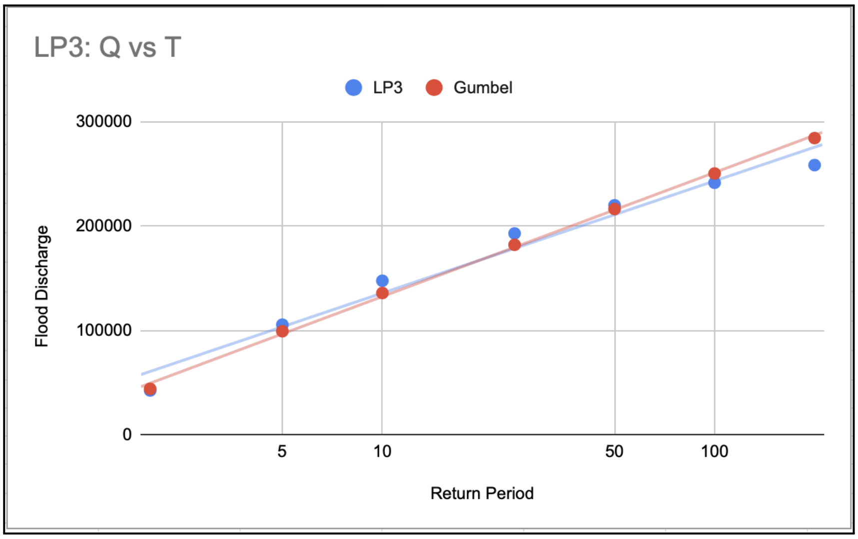
Log-Pearson Type III Distribution Results

Observed discharge values are first transformed using logarithms for computation. The skewness coefficient was calculated as -1.2397. Expected peak flood discharges were computed for different return periods:

Log10(Q)	Log10(Q)-av	(Log10(Q)-av)^2	(Log10(Q)-av)^3
5.168638886	0.6675344053	0.4456021823	0.2974547878
4.920952496	0.4198480153	0.1762723559	0.07400759878
4.878831895	0.3777274143	0.1426779995	0.05389339184
4.84509804	0.3439935592	0.1183315688	0.04070529752
4.727012299	0.2259078186	0.05103434252	0.01152905699
4.613249679	0.1121451982	0.01257654547	0.001410399184
4.354338977	-0.146765504	0.02154011316	-0.00316134556
3.728353782	-0.7727506988	0.5971436424	-0.461443167
3.273464273	-1.227640208	1.507100481	-1.850177148
	sum	3.072279231	-1.835781128
N	9		
mean	4.501104481		
std dev	0.6197054977		
skew	-1.239707808		
Cs	-1.239707808		

T	Kz	zT	Q
2	0.2009561712	4.625638125	42231.65731
5	0.8416175315	5.022659492	105356.053
10	1.077264282	5.168691079	147465.7211
25	1.265322721	5.285231927	192855.4548
50	1.357160706	5.342144431	219859.0926
100	1.422792847	5.38281703	241444.3405
200	1.470424988	5.41233493	258425.2408





R-Based Calculations

The R code for analysis has been uploaded to this repository:
https://github.com/megz15/hydrology-ffa/

Distribution Fitting Results

The table below depicts the discharge values estimated for various return periods using five probability distributions fitted to the Nizam Sagar AMS data.

T	Gumbel_MLE	Gumbel_Manual	LogNormal_Manual	LogNormal_MLE	LP3_MLE	Weibull_MLE	Gamma_MLE
2	47,964.65	49,470.45	31,703.30	31,703.30	42,574.23	40,842.60	38,907.47
5	89,748.35	103,730.24	105,356.61	98,363.38	74,265.39	88,566.05	89,364.91
10	116,080.70	139,654.93	197,373.59	177,774.25	94,965.12	123,078.98	127,372.16
25	147,907.27	185,045.89	385,491.02	334,169.83	136,377.42	167,441.66	177,514.55
50	170,518.90	218,719.49	594,051.33	502,384.14	194,021.14	200,302.37	215,398.82
100	192,155.71	252,144.45	876,506.31	724,946.02	301,029.17	232,691.30	253,255.54
200	212,941.86	285,447.45	1,251,296.01	1,014,071.73	513,676.03	264,685.39	291,091.57

Observations:

1. Using the Gumbel distribution manually in Excel predicted 34% higher discharge than MLE at T=200. This could be due to the incorporation of skewness adjustments or overweighting of extreme events during manual parameterisation, while complete dependence on data-driven optimisation is followed during MLE.
2. Similarly, Manual Log-Normal estimates double the MLE value at T=200. A probable reason is that manual fitting might have overemphasised upper-tail behaviour, whereas MLE constrains growth via sample moments.
3. LP3 discharge triples between T=50 and T=200, surpassing other methods, probably due to better capture of heavy-tailed distributions common in extreme floods.
4. At T=50, Gamma and Weibull differ by only ±7.5%. This can be due to a shared gamma-family foundation, converging when moderate annual series skewness is present and sufficient record lengths stabilise the moment estimate.

Inference:

1. Inherent subjectivity in curve-fitting is suggested by the observed overprediction by manual Gumbel and Log-Normal methods, thereby advocating for MLE to reduce human bias in critical infrastructure design.
2. The spread between Log-Normal Manual and LP3 at T=200 emphasises the risks of single-model approaches for rare floods, suggesting multi-model ensembles for robust risk assessment.
3. LP3's use for infrastructure with >100-year lifespans is validated by the alignment of its progressive acceleration with observed parabolic growth in partial-duration series (PDS) of extreme floods.

Goodness of Fit Test Results

The table below presents the results of the Kolmogorov-Smirnov and Anderson-Darling tests performed on the used distributions.

Distribution	KS_Statistic	KS_PValue	AD_Statistic	AD_PValue
Gamma	0.1856	0.8629	0.3724	0.8727
Gumbel	0.1321	0.991	0.1979	0.9917
Log-Normal	0.2428	0.5832	0.6356	0.6103
Weibull	0.1685	0.9248	0.3797	0.8656

Observations:

1. Gumbel shows the lowest KS statistic (0.1321) and highest p-values (KS: 0.991, AD: 0.9917) among all distributions. This is possibly since the Gumbel distribution is specifically designed for extreme value modelling, suggesting the flood data likely follows type I extreme value patterns.
2. Log-Normal exhibits the highest KS statistic (0.2428) and lowest p-values (KS: 0.5832, AD: 0.6103). This could be due to a lower coefficient of variation in the dataset than Log-Normal can effectively model, or the true distribution having a different tail behaviour than the logarithmic transformation can accommodate.
3. Gamma and Weibull show intermediate statistics with comparable values. These distributions share flexible shape parameters that adapt similarly to moderate positive

skewness typically found in annual flood series, which could have led to a parallel performance.

4. All distributions have p-values substantially above the typical 0.05 threshold for both KS and AD tests. This implies that the dataset likely has a moderate sample size with limited outliers, allowing multiple theoretical distributions to provide statistically acceptable fits despite their mathematical differences.

Inferences:

1. Due to the strong favour by both goodness-of-fit tests, the Gumbel distribution should be prioritised for flood frequency modelling in this watershed.
2. The importance of extreme value prediction accuracy is highlighted by the greater discrimination by the Anderson-Darling test between distributions than the KS test.
3. For engineering applications, distributions can be ranked: Gumbel > Weibull > Gamma > Log-Normal
4. The exceptionally high p-values for Gumbel (>0.99) provide strong statistical justification for its use in regulatory floodplain mapping and infrastructure design.

<u>Performance Metrics Results</u>

The table below displays the results of performance metrics applied to all the methods utilised.

Distribution	RMSE	NSE	KGE
Gumbel (MME)	8780.18	0.958	0.9575
Gumbel (MLE)	12032.41	0.9212	0.7968
Log-Normal (MME)	22519.84	0.7239	0.6309
Log-Normal (MLE)	17697.5	0.8295	0.7658
LP3	20106.53	0.7799	0.5863
Gamma (MLE)	12024.44	0.9213	0.8254
Weibull (MLE)	12245.4	0.9184	0.8013

Observations:

1. Gumbel (MME) demonstrates the lowest RMSE (8780.18) and highest NSE (0.958) and KGE (0.9575) values among all distributions. This is likely due to the possibility of the flood data following a classic Type I extreme value pattern that the Gumbel distribution is specifically designed to model.

2. Log-Normal (MME) shows the highest RMSE (22519.84) and lowest NSE (0.7239), indicating the poorest fit. This is because the watershed likely experiences flooding mechanisms that don't follow logarithmic patterns that the Log-Normal distribution best represents.
3. For the same distribution families, MME and MLE show substantial performance differences, possibly due to the prioritisation of matching statistical moments directly by MME, while optimisation of likelihood by MLE, with this dataset containing characteristics that favour moment-matching approaches.
4. LP3 shows high RMSE (20106.53) yet moderate NSE (0.7799) with the lowest KGE (0.5863). This mght be due lack of pronounced skewness in the watershed, a parameter that LP3 is designed to capture, causing the distribution to overcompensate and misrepresent variability components measured by KGE.

Inferences:

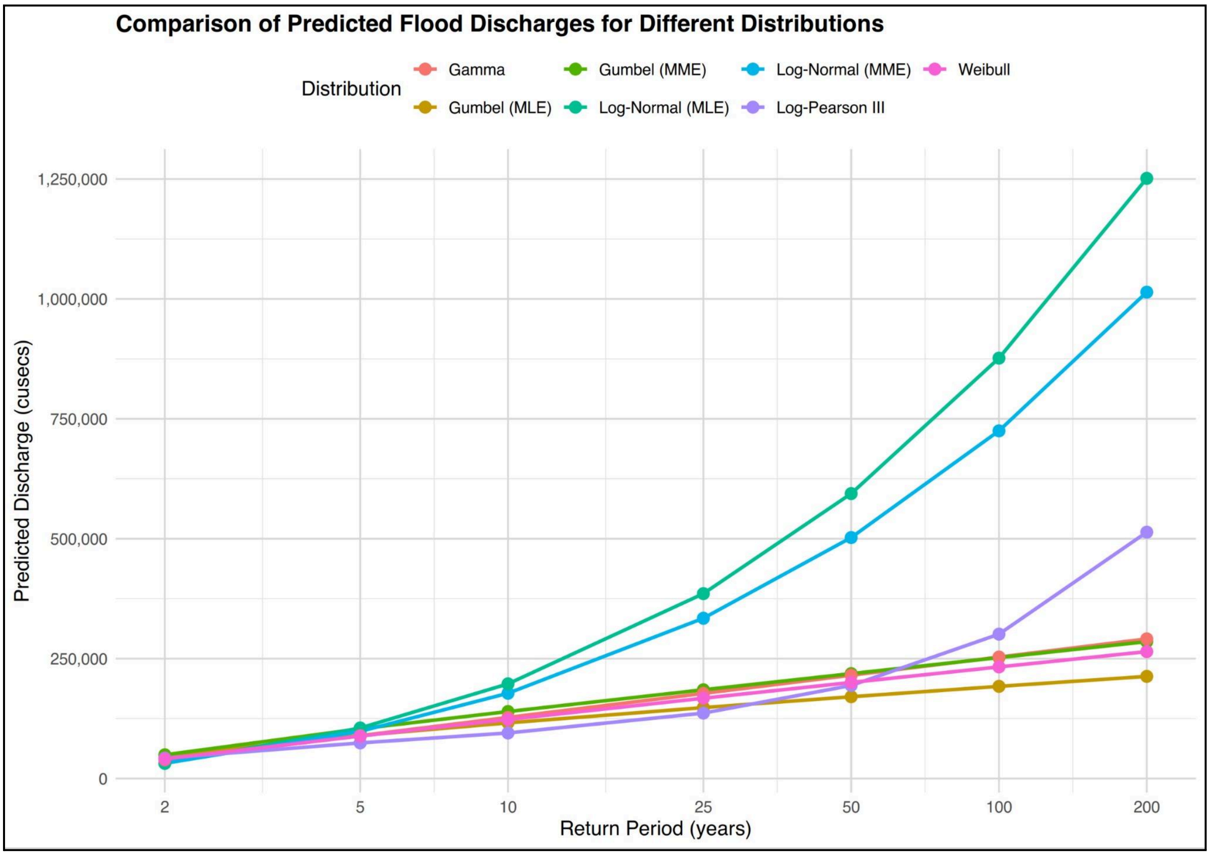
1. Due to superior performance, Gumbel (MME) should be the primary choice for flood frequency modelling in this watershed.
2. Engineering applications should prioritise MME approaches for this dataset.
3. For practical implementation, distributions can be ranked as: Gumbel (MME) > Gumbel (MLE) ≈ Gamma (MLE) ≈ Weibull (MLE) > Log-Normal (MLE) > LP3 > Log-Normal (MME)

<u>Comparative Analysis</u>

1. Gumbel demonstrates superior statistical performance (lowest KS: 0.1321, highest p-value: 0.991) and best-fitting metrics (RMSE: 8780.18, NSE: 0.958). This suggests that the watershed experiences flooding mechanisms which follow classic extreme value theory patterns, making Gumbel the most reliable distribution.

2. The 5-fold range in extreme flood estimates has substantial economic implications, as infrastructure designed using Log-Normal models would require dramatically larger capacity than those using Gumbel models.

3. Method of Moments Estimation (MME) consistently outperforms Maximum Likelihood Estimation (MLE) for the Gumbel distribution, while depicting opposite effects for Log-Normal models. This suggests that for this watershed's specific



statistical characteristics, MME better captures the central tendency of flood behaviours.

4. The major divergence between statistically acceptable models at high return periods (T>50) highlights the critical importance of employing multiple evaluation metrics rather than relying solely on goodness-of-fit tests. While all distributions pass standard statistical tests (p>0.05), their practical predictions vary by orders of magnitude, reinforcing that flood frequency analysis requires both statistical rigour and hydrological reasoning to ensure physically plausible design flows.

CONCLUSION

A comprehensive statistical evaluation and comparative analysis demonstrates the Gumbel distribution with Method of Moments Estimation as the optimal statistical model for flood frequency analysis in this watershed due to the best performance across all evaluation metrics (RMSE: 8780.18, NSE: 0.958, KGE: 0.9575) and the highest goodness-of-fit validation (KS p-value: 0.991, AD p-value: 0.9917). The pronounced divergence between probability distributions at higher return periods, where Log-Normal distributions predict discharge values approximately five times greater than Gumbel-based estimates at the 200-year return period, thus underscores the necessity of an efficient model selection in hydrological engineering applications. While all distributions satisfy conventional statistical acceptance criteria, their differences in extrapolation behaviour have critical implications for infrastructure design, economic feasibility, and risk management. The implementation of Log-Normal distributions would necessitate considerably larger hydraulic structures compared to Gumbel-based designs, potentially resulting in unnecessary expenditure without commensurate safety benefits. Furthermore, the parameter estimation methodology demonstrates significant influence on prediction outcomes, with MME consistently outperforming MLE for the Gumbel distribution in this particular watershed context. These findings emphasize the importance of employing multiple evaluation criteria and considering both statistical validity and physical plausibility when conducting flood frequency analysis for critical infrastructure design and flood risk management.

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