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Analyzing Extreme Water Volume Events in Khwae Noi Bamrung Daen Dam: A Statistical Approach

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Abstract. This study focuses on the statistical modeling of extreme water volumes at the Kwae Noi Bamrung Daen Dam in Phitsanulok Province using extreme value theory (EVT). The objective is to predict high water levels that may pose risks to dam safety and operations. Historical monthly water volume data from 2011 to 2023 were analyzed using the generalized extreme value (GEV) distribution. The Jarque-Bera test confirmed a non-normal distribution (p = 0.02906), justifying the use of EVT. Maximum likelihood estimation yielded parameter estimates of μ = 446.58, σ = 228.68, and ξ = -0.13. Goodness-of-fit tests (K-S and A-D) confirmed the adequacy of the GEV model, with p-values of 0.3559 and 0.1124, respectively. The model estimated that extreme water volumes exceeding 950 million cubic meters are expected approximately once every 25 years. These findings contribute to more accurate hydrological forecasting, improved early warning systems, and enhanced water resource management policies. The study supports risk-informed decision-making in flood-prone regions and advances the application of EVT in dam safety and environmental planning.

1. Introduction

His Majesty the Late King Bhumibol Adulyadej initiated the Khwae Noi Bamrung Daen Dam project to alleviate flooding problems in the lower Kwai Noi River basin and to serve as a water source for agriculture, consumption, and general cultivation during both the rainy and dry seasons. The reservoir area at the storage level is 61.39 square kilometers, with a capacity at the normal storage level of 939 million cubic meters. However, the construction of a dam necessitates

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management to ensure its ability to store and supply water for consumption. In 2016, Richard Minkah [1] noted that events related to dam management, such as low or extremely high water volumes, can significantly impact the dam's operation. If the impact is not significant, it will lead to a partial dam shutdown, and in severe cases, it will result in a complete shutdown of the system. On the other hand, it could potentially lead to flooding as a result of excess water leakage or, in the worst-case scenario, dam breakage. Either way, the impact can result in disasters affecting energy, the environment, life, and property [2–7]. Therefore, modeling and estimating the frequency of these events remains an important issue for engineers and dam managers. This research studies the application of extreme value theory (EVT), which is the basis for statistical analysis of extremely high water volumes that may adversely affect or impact the operation of a dam.

The statistical technique, known as extreme value analysis (EVA), predicts the likelihood of extreme values in data of interest and identifies the risk of infrequent events, like excessive rainfall, flooding, extreme weather conditions, or severe storms. Numerous disciplines, including engineering, communication, finance, risk management, insurance, economics, materials science, hydrology, meteorology, and others, widely utilize the technique. We use historical data to find the parameters of the extreme value (EV) by finding the highest values of random variables that are the same and not connected to each other. The EV has been applied to a significant amount of real-world data [8–15]. The research study reveals the critical role of mathematical and statistical estimation in analyzing changing data. These types of data are characterized by extreme values. Consequently, we can develop a model to predict water volume data based on the occurrence of extreme values. We can then analyze this data to create a forecast model that identifies the highest event values. This results in a favorable warning model. When there is a successful warning model, it will lead to the creation of successful management policies. Fuller first applied the EVT in 1914 [16], followed by Saraless Nadarajah and Dongseok Choi [17], and also, researchers like Piyaphat Busababodin and Arun Kaewman [18] have looked into EV statistics, used EVT on real data from different fields, discussed the idea and history of extreme value theory, and compiled a list of the inferential statistics of extreme values. EV distributions, such as GEV distributions and generalized Pareto distributions, etc. We also looked at extreme value distributions, like GEV distributions and generalized Pareto distributions, to see if they were useful and to find out how often they happened and how often they happened each year. We utilized mathematical models of forecasting, specifically the GEV distribution, to estimate parameters, return period, and return level. There is also research that applies EV to various works related to natural disasters [19–24].

Therefore, the researchers propose to analyze and compare appropriate distributions to create a probability model based on the water volume of the Kwae Noi Bamrung Daen Dam. The research aims to forecast the water volume in the dam using mathematical and statistical forecasting models to ensure accuracy. To ensure smooth operations, they also want to find out what the government's rules are and how related agencies handle water management at the Khwae Noi Bamrung Daen

Dam in Phitsanulok province. The goal is to increase the efficiency of the Khwae Noi Bamrung Daen Dam in Phitsanulok province.

2. Extreme Value Theory

Based on the extreme value theory, we generalized the extreme value distribution, the details of which are as follows

Let $X_1, X_2, \ldots, X_n$ be a sequence of independent and identically distributed random variables with a common distribution function F. Suppose that M_n represents the maximum of these variables for all values of n, defined by

$$M_n = \max(X_1, X_2, \ldots, X_n).$$

If n is the number of observations in a year, then M_n represents the annual maximum. The distribution M_n can be derived exactly for all values of n as follows:

$$\begin{aligned} P\{M_n \le z\} &= P\{X_1 \le z, X_2 \le z, \ldots, X_n \le z\} \\ &= P\{X_1 \le z\} \times P\{X_2 \le z\} \times \cdots \times P\{X_n \le z\} \\ &= [F(z)]^n. \end{aligned}$$

Thus, we have $P\{M_n \le z\} = [F(z)]^n$. As $n \to \infty$, the finite maxima M_n converges to the upper endpoint of F. To analyze the behavior of $F^n(z)$ as $n \to \infty$, suppose there exist sequences of normalizing constants $a_n > 0$ and $b_n \in \mathbb{R}$ such that

$$P\left(\frac{M_n - b_n}{a_n} \le z\right) = F^n(a_n z + b_n) \longrightarrow GEV(z),$$

where GEV is the non-degenerated distribution function. According to the EVT, the limiting distribution $GEV(z)$ belongs to one of the three types, collectively known as the GEV distribution, defined as

$$GEV(z) = \exp\left\{-\left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\},$$

for $1 + \xi\left(\frac{z-\mu}{\sigma}\right) > 0$, where $\mu \in \mathbb{R}$ is the location parameter, $\sigma > 0$ is the scale parameter, and $\xi \in \mathbb{R}$ is the shape parameter. Special cases of the GEV distribution include

(1) **Gumbel Type (Type I)**: When $\xi = 0$,

$$GEV(z) = \exp\left\{-\exp\left(-\frac{z-\mu}{\sigma}\right)\right\}.$$

(2) **Fréchet Type (Type II)**: When $\xi > 0$,

$$GEV(z) = \begin{cases} 0, & \text{if } z \le \mu - \frac{\sigma}{\xi}, \\ \exp\left\{-\left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, & \text{if } z > \mu - \frac{\sigma}{\xi}. \end{cases}$$

(3) **Weibull Type (Type III)**: When $\xi < 0$,

$$GEV(z) = \begin{cases} \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, & \text{if } z < \mu - \frac{\sigma}{\xi}, \\ 1, & \text{if } z \geq \mu - \frac{\sigma}{\xi}. \end{cases}$$

Therefore, under appropriate normalization, the distribution of the maximum M_n converges to one of these extreme value distributions $GEV(z)$ as $n \to \infty$.

The estimates of extreme quantiles x_p of the GEV distribution are obtained by inverting the cumulative distribution function $GEV(x; \mu, \sigma, \xi)$. This yields

$$x_p = \begin{cases} \mu + \frac{\sigma}{\xi}\left([-\log(p)]^{-\xi} - 1\right), & \xi \neq 0, \\ \mu - \sigma \log[-\log(p)], & \xi \to 0. \end{cases} \tag{2.1}$$

Estimating the unknown parameters of the GEV distribution involves finding the Maximum Likelihood Estimation (MLE) of the parameters μ, σ, and ξ. The likelihood function $L(\mu, \sigma, \xi)$ for the GEV distribution can be written as

$$\begin{aligned} L(\mu,\sigma,\xi) &= \prod_{i=1}^{n}\left(\frac{1}{\sigma}\left(1+\xi\frac{z_i-\mu}{\sigma}\right)^{-1/\xi-1}\exp\left(-\left(1+\xi\frac{z_i-\mu}{\sigma}\right)^{-1/\xi}\right)\right) \\ &= \frac{1}{\sigma^n}\prod_{i=1}^{n}\left(1+\xi\frac{z_i-\mu}{\sigma}\right)^{-1/\xi-1}\exp\left(-\left(1+\xi\frac{z_i-\mu}{\sigma}\right)^{-1/\xi}\right), \end{aligned} \tag{2.2}$$

and the log-likelihood function $l(\mu, \sigma, \xi)$ is

$$l(\mu,\sigma,\xi) = -n\log\sigma - \left(1+\frac{1}{\xi}\right)\sum_{i=1}^{n}\log\left(1+\xi\frac{z_i-\mu}{\sigma}\right) - \sum_{i=1}^{n}\left(1+\xi\frac{z_i-\mu}{\sigma}\right)^{-1/\xi}, \tag{2.3}$$

where $1 + \xi\frac{z_i - \mu}{\sigma} > 0$ and $\xi \neq 0$.

Return levels (RL) can be calculated for a given return period (T) using the GEV distribution as follows:

$$RL = \mu - \frac{\sigma}{\xi}\left(1 - \left(-\log\left(1-\frac{1}{T}\right)\right)^{-\xi}\right), \tag{2.4}$$

for $T = N \times n_y$ when n_y is one observation per year, and N is the number of years.

The confidence interval of the RL for the GEV distribution is derived using the Delta method as follows:

$$\text{Var}(RL) \approx \nabla RL^T \, \Sigma \, \nabla RL, \tag{2.5}$$

where Σ is the covariance matrix of $(\mu, \sigma, \xi)^T$ and

$$\nabla RL = \left[\frac{\partial RL}{\partial \mu}, \frac{\partial RL}{\partial \sigma}, \frac{\partial RL}{\partial \xi}\right]^T.$$

The partial derivatives are $\frac{\partial RL}{\partial \mu} = 1$, $\frac{\partial RL}{\partial \sigma} = -\frac{1}{\xi}\left(1 - T^{-\xi}\right)$, $\frac{\partial RL}{\partial \xi} = \sigma\xi^{-2}\left(1 - T^{-\xi}\right) - \sigma\xi^{-1}T^{-\xi}\log T$.

The Wald method is commonly used to construct confidence intervals for parameters of interest. In the context of extreme value analysis with the GEV distribution, the Wald confidence interval for the RL is implemented as

$$RL \pm Z_{\alpha/2} \times \sqrt{\mathrm{Var}(RL)},$$

where $\mathrm{Var}(RL)$ is the estimated variance from the Delta method, and $Z_{\alpha/2}$ is the standard normal quantile corresponding to the desired confidence level.

3. Data and Research Methodology

The study area domain includes his Majesty the Late King Bhumibol Adulyadej the Great, who initiated the Khwae Noi Bamrung Daen Dam Project to alleviate flooding in the lower Khwae Noi River basin and serve as a water source for general agriculture during the rainy and dry seasons and for personal consumption. The reservoir has an area of 61.39 square kilometers and can normally hold 939 million cubic meters of water. It provides water to 155,166 rai of farmland in Wat Bot District, Wang Thong District, Mueang Phitsanulok District, and Bang Krathum District, in Phitsanulok Province. It also blocks the Khwae Noi River, as shown in Figure 1.

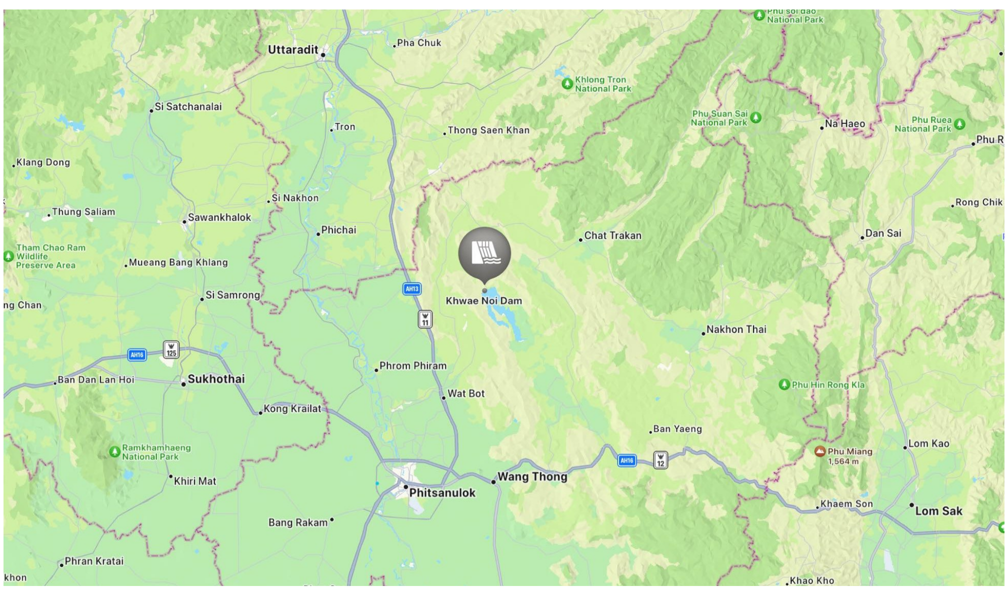

Figure 1. Study site with locations of Khwae Noi Bamrung Daen Dam.

The study used monthly maximum water volumes from the Office of Irrigation Region 3 of the Royal Irrigation Department of Phitsanulok province from 2011 to 2023. The data set comprises 156 observations of the maximum monthly water volumes. We used the MLE method to fit the sample data to the GEV distribution and then performed an extreme value analysis. The GEV distribution encompasses the following families of distributions: Gumbel Distribution (Type I), Fréchet Distribution (Type II), and Weibull Distribution (Type III).

For statistical analysis, we employed the `extRemes` package in R, developed by Gilleland et al. [11], which facilitates parametric inferential analysis of the GEV distribution. This package was instrumental in estimating the parameters and assessing the goodness-of-fit for the data obtained from the Office of Irrigation Region 3, Royal Irrigation Department. The steps are as follows and are summarized in Algorithm 1, which presents a structured procedure for fitting the GEV distribution to the observed extreme water volume data, including parameter estimation, goodness-of-fit testing, and return level computation.

3.1. **Analysis of the generalized extreme value distribution.** The analysis is based on the data available from the water volumes of the Khwae Noi Bamrung Daen Dam. The Office of Irrigation Region 3 of the Royal Irrigation Department of Phitsanulok Province recorded the data, which were the maximum available monthly water volumes, from 2011 to 2023. The statistical summary shows that the data consist of 156 monthly observations. The maximum monthly water volume recorded was 980.31 million cubic meters, with a mean of 555.58 and a standard deviation of 260.46. The coefficient of skewness is 0.276, suggesting a slight positive skew in the distribution. The Jarque-Bera test statistic is 7.0768 with a p-value of 0.02906, indicating a statistically significant departure from normality. Hence, the data exhibit characteristics of a non-normal distribution, justifying the use of generalized extreme value modeling in further analysis.

Table 1. Maximum likelihood estimates (standard errors) of the GEV distribution parameters

	Location (μ)	Scale (σ)	Shape (ξ)
Estimation	446.58	228.68	-0.13
Standard errors	32.86	26.76	0.17
CI 95%	(384.84,515.50)	(177.47,284.00)	$(-0.48, 0.19)$

Table 1 indicates the results of the GEV modeling on the extreme water volumes in Khwae Noi Bamrung Daen Dam using the Block Maxima approach. The GEV parameters were estimated using MLE. The estimated results are (μ, σ, ξ) = (446.58, 228.68, −0.13), with standard errors (32.86, 26.76, 0.17). The approximate 95% confidence intervals (CI) for the parameters are thus (384.84,515.50) for μ, (177.47,284.00) for σ, and $(-0.48, 0.19)$ for ξ. Since the confidence intervals ξ contain 0, the Gumbel distribution is the optimal model for the GEV family.

3.2. **Goodness-of-fit tests.** The quality of convergence of the water volume extremes is accessed using the Kolmogorov-Smirnov (K-S) and Anderson-Darling (AD) for goodness-of-fit tests. The K-S and AD test, relying on the empirical study of the cumulative distribution function, are used to determine if the sample is from the hypothesized continuous distribution, as shown in Table 2.

In Table 2 shows the K-S and AD test approaches are less sensitive for normal distribution. The assumption is that the data is from a population independent of identical distribution (i.i.d.). The alternative hypothesis is a two-tail test, assuming that the data follow a monotonic trend.

Algorithm 3.1 GEV-Based EVT Modeling for Extreme Water Volumes

Input: Monthly maximum water volume data $X = \{x_1, x_2, ..., x_n\}$ (2011–2023)

Output: Return levels RL_T for return periods $T = \{2, 5, 10, 15, 20, 25, 50, 100\}$

Step 1: Data Preparation
Load the monthly maximum water volumes from the Royal Irrigation Department ;

Step 2: Preliminary Analysis
Compute mean, standard deviation, skewness ;
Perform Jarque–Bera normality test ;
if p-value < 0.05 **then**
  Proceed with EVT modeling ;
else
  Consider data transformation or alternative modeling approach ;
end if

Step 3: GEV Parameter Estimation
Fit the GEV distribution using Maximum Likelihood Estimation (MLE) ;
Estimate parameters: μ, σ, and ξ ;
Compute 95% confidence intervals for each parameter ;

Step 4: Goodness-of-Fit Assessment
Conduct Kolmogorov–Smirnov (K–S) and Anderson–Darling (A–D) tests ;
if p-values > 0.05 **then**
  Accept the GEV model fit ;
else
  Reconsider model or refine estimation ;
end if

Step 5: Return Level Calculation
for Return period $T \in \{2, 5, 10, 15, 20, 25, 50, 100\}$ **do**
  Compute return level using:

$$RL_T = \mu - \frac{\sigma}{\xi}\left(1 - [-\log(1 - \tfrac{1}{T})]^{-\xi}\right)$$

  Compute 95% confidence interval using the Delta method ;
end for

Step 6: Diagnostic Plotting and Interpretation
Generate probability, quantile, return level, and density plots ;
Interpret return levels and compare with dam capacity and risk thresholds ;

Step 7: Conclusion and Application
Discuss implications for flood forecasting and dam safety policy ;

Table 2. K-S and AD tests to determine whether the monthly highest water volumes of Khwae Noi Bamrung Daen Dam from 2011 – 2023 follow a GEV distribution

Test	Test statistic	p-value
K-S	0.0994	0.3559
AD	1.8424	0.1124

Therefore, from the results obtained, the p-value of the K-S test is 0.3559, and the AD test is 0.1124. Thus, the parameter estimate by GEV distribution is appropriate for this dataset.

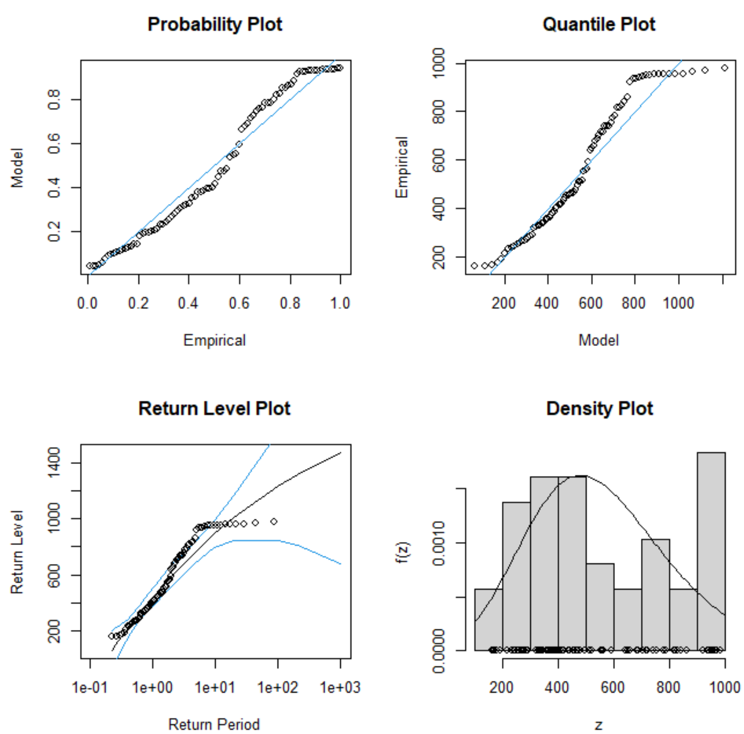

Figure 2. The normal probability density function of the monthly highest water volumes of Khwae Noi Bamrung Daen Dam from 2011-2023 following a GEV distribution.

Figure 2 shows the diagnostic plots for the GEV distribution. The probability plot and quantile plot points lie close to the diagonal unit. This implies that the GEV distribution function provides a good fit. The return level plot shows that the empirical return levels match well with those from the fitted distribution function. Finally, the density plot shows good agreement between the fitted GEV distribution function and the empirical density.

Table 3 shows the estimated return periods of maximum water volumes likely to occur over the next 2, 5, 10, 15, 20, 25, 50, or even 100 years fitted by GEV distribution. The RL are concerning the change in return periods. Changes in increasing return periods and return levels of extreme maximum water volumes also increase, as shown in Figure 3. When considering the water volume

Table 3. Return level estimates (Mm^3) at selected return periods determined by using the GEV distribution

Return periods	RL estimate	CI (95%)
2	532.4758	(459.2254, 605.7262)
5	760.3927	(686.4787, 834.3068)
10	891.4896	(796.6583, 986.3209)
15	891.4896	(796.6583, 986.3209)
20	1004.2182	(848.8149, 1159.6216)
25	1037.5296	(856.7392, 1218.32)
50	1133.3191	(861.7674, 1404.8707)
100	1218.9937	(843.9002, 1594.0871)

estimation data, it is found that the Khwae Noi Bamrung Daen Dam can support the water volume in every estimation period. For example, in a 100-year period, the water volume is 1218.9937 Mm^3, and the 95% confidence interval is (843.9002, 1594.0871). Therefore, in a 100-year period, if there is proper management of the rising water volume, the Khwae Noi Bamrung Daen Dam can well support the water volume in this 100-year period.

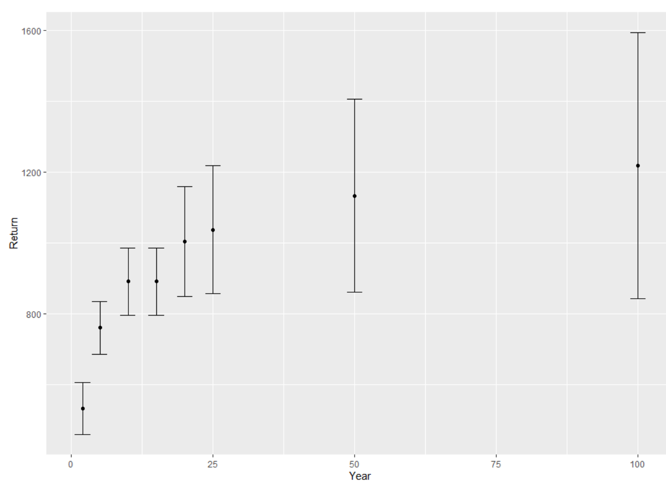

Figure 3. The return levels of maximum water volume for Khwae Noi Bamrung Daen Dam in all return periods for GEV distribution.

4. Conclusions

Using the EVT, the study will provide information on how high water volumes behave, using data from the Royal Irrigation Department's Office of Irrigation Region 3 in Phitsanulok province. The findings of this study can also be used by governmental or non-governmental groups to inform their planning and decision-making in order to better prepare the public for the changes that the highest water volumes will bring about. In the present study, we used high water volumes from

2011 to 2023. GEV distribution analysis was then used to examine the data. The calculation of parameters for the return level for water volumes for 2, 5, 10, 15, 20, 25, 50, and 100 years was thus obtained from the GEV distribution.

The estimated shape parameter ($\xi = -0.13$) indicated a light tail behavior, suggesting that although extreme events can occur, their magnitude may be moderately bounded. The Kolmogorov-Smirnov and Anderson-Darling tests yielded p-values of 0.3559 and 0.1124, respectively, confirming that the GEV distribution is a statistically adequate fit for the dataset. A 25-year return level was estimated at approximately 950 million cubic meters, which is notably higher than the observed mean, emphasizing the need for robust planning against rare but impactful events. These findings directly align with the study's objective to identify the statistical behavior of extreme water volumes and enhance dam operation safety.

Compared to previous studies conducted in similar hydrological settings, our results reinforce the applicability of EVT-based models in tropical monsoon-influenced regions. Fields such as early warning systems, food security, poverty reduction, disaster management, and risk management can benefit from the study by enabling timely decision-making. To increase knowledge and the effectiveness of existing theories, we can also create an extended framework for extreme value modeling, potentially adapting the methodology to other environmental domains or geographic regions.

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