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Assessing Flood Risk Using L-Moments: An Analysis of the Generalized Logistic Distribution and the Generalized Extreme Value Distribution at Sayong River Station

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ABSTRACT

This study examines severe flood events at Sayong River Station by conducting a Flood Frequency Analysis using the Generalized Logistic (GLO) and Generalized Extreme Value (GEV) distributions. The L-moment approach is utilized for parameter estimation, with quantile estimates assessed for return periods of 10, 50, and 100 years. A comprehensive comparison of statistical performance indicators, such as RMSE, MAE, and MAPE, was performed to identify the best realistic model for depicting severe flood behavior. The findings indicate that the GLO distribution consistently outperforms the GEV distribution in all criteria. The GLO distribution demonstrated superior performance with a lower RMSE (17.7369), MAE (8.6608), and MAPE (11.83%) relative to the GEV distribution, which exhibited an RMSE of 17.8034, MAE of 8.7957, and MAPE of 12.98%. These findings validate the GLO distribution as the better appropriate model for representing peak streamflow data. Moreover, quantile estimates obtained from the GLO distribution are197.3153 m^3/s for the 10-year, 363.8308 m^3/s for the 50-year and 469.9711 m^3/s for the 100-year return periods. The GLO distribution exhibit greater concordance with empirical data, further validating its accuracy. The superior performance of the GLO distribution emphasizes the importance of selecting the appropriate distribution for flood risk assessment. The GLO distribution yields more accurate predictions of severe flood magnitudes, hence enhancing flood estimations, infrastructure design, and mitigation measures at Sayong River Station.

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1. Introduction

Natural disasters like floods are very destructive in Malaysia, causing damage on lives of individuals, agricultural products, and infrastructure [1-3]. The nature of environment in Malaysia characterized by monsoonal rainfall and frequent thunderstorms, makes it particularly vulnerable to flash floods [4]. During periods of intense precipitation or severe weather phenomena, the river is prone to flooding, which can affect the community, infrastructure, and the surrounding environment. Given the circumstances, there is an urgent need for accurate assessment and water resource management.

Flood Frequency Analysis (FFA) is an essential tool can be used to the estimate the probability and scale of future flood occurrences [5]. FFA provides essential insights into the likelihood and severity of flooding events. By estimating the frequency and magnitude of extreme floods, stakeholders can better understand the risks associated with flood hazards, enabling them to implement appropriate mitigation measures. As climate change continues to influence weather patterns and hydrological systems, FFA can provide insights into changing flood risks [6]. This helps communities adapt to new flood dynamics, informing strategies for resilience in the face of climate-related challenges.

Currently, there is ongoing interest in determining the optimal distribution for FFA. Researchers are exploring various statistical models, such as the Gumbel, Log-Pearson Type III, and Generalized Extreme Value distributions, to identify which model best fits historical flood data. A significant method gaining traction in this context is the use of L-Moments, which offer a robust alternative to traditional moment-based approaches. Moreover, the integration of L-Moments into the FFA process allows for the calculation of key statistical measures, such as the L-CV (L-Coefficient of Variation) and L-Skewness. These measures provide insights into the distribution of flood data, enhancing the understanding of flood risk and facilitating more accurate flood modelling.

By applying these methodologies, researchers can develop a more nuanced understanding of the underlying hydrological processes that contribute to flooding. Current research efforts are focused on determining the optimal statistical distributions for FFA, which can significantly enhance the accuracy of flood predictions. By refining these methodologies, researchers aim to improve the reliability of flood frequency estimates, enabling more effective disaster preparedness and response initiatives.

2. Literature Review

Through the use of historical flood data, FFA allows researchers and policymakers to evaluate the probability of flood events occurring within a specified time frame, known as return periods at targeted location [7]. Precise estimations of these return period are essential for effective flood- mitigating planning and strategic emergency responses management. FFA is particularly crucial in Malaysia, given the potential for floods to inflict significant damage on both rural and urban areas [8]. The necessity to adjust to the changing precipitation pattern and flood behaviors driven by climate change further highlights the significance of FFA.

This paper aims to conduct FFA for the Sayong River in Johor, Malaysia, utilizing two most implemented distribution in Malaysia namely GEV and GLO distributions for peak streamflow data [9],[10]. This study presents a thorough comparison between the Generalized Extreme Value (GEV) and Generalized Logistic (GLO) distributions in modelling flood events in Malaysia. The analysis reveals the relative strengths and weaknesses of each distribution, providing valuable insights into their applicability in different hydrological contexts. FFA plays a critical role in assessing flood risks, especially in regions like Malaysia, where extreme hydrological events are frequent.

The GEV and GLO distributions are often used in FFA because of their adaptability and resilience in representing extreme hydrological occurrences [10-12]. The GEV distribution comprising Gumbel, Fréchet, and Weibull distributions. The GEV and GLO distributions are often used statistical distributions in FFA because of their adaptability and resilience in representing extreme hydrological occurrences [11-13]. The GEV distribution comprises three unique statistical distributions: Gumbel, Fréchet, and Weibull distributions [14]. The GEV distribution offers flexibility in handling hydrological data and is valuable for evaluating extreme event likelihood by considering block maxima in datasets [15]. It is particularly suitable for analyzing yearly maximum flood levels and has been proven suitable in FFA. The GEV distribution is specifically designed to model the distribution of extreme values, making it ideal for analyzing peak flows, which are critical for flood risk assessment and management. It is well-suited for analyzing yearly maximum flood levels and has been proven suitable in FFA.

The GLO distribution recognized for its logistic-type tail characteristics, provides an alternative approach for modelling extreme events, especially when the data exhibits asymmetry or heavy tails [16]. Previous studies in Peninsular Malaysia have utilized various statistical distributions to measure flood frequency, with GEV and GLO distributions being the most used options for FFA in Malaysia. Ahmad *et al.* [9] finds that the Generalized Extreme Value (GEV) distribution model is the best-fitted flood distribution model for the Kuantan River Basin, with a P-value of 0.997 compare to other distributions such as Generalized Pareto distribution, Log Pearson (3) distribution, Weibull distribution and Log-normal distribution.

Badyalina *et al.* [17] implement GEV and GLO distribution to fit to the annual peak streamflow for the Segamat river. In addition, the parameters of GEV and GLO distribution are estimated using the L-Moment method. The result shows that the GEV and GLO distribution well fitted the annual peak streamflow of the Segamat River. Ismail *et al.* [18] examines and compares five flood distribution models for the Johor River basin in Malaysia. The investigation suggests that the GEV model is the most suitable for representing the yearly peak flow data. The GEV model outperformed other distributions such as Pearson 3, Lognormal, Weibull, and Gamma.

The GLO distribution is particularly effective for modelling extreme flood events, which are often characterized by high variability and non-normality [19]. Its ability to capture the tail behavior of the data is crucial for accurate flood frequency analysis. Malaysia experiences a tropical climate characterized by intense and irregular rainfall patterns, leading to sudden and extreme flood events. The GEV and GLO distribution can effectively capture the behavior of such extreme hydrological data.

A key aspect of FFA is the precise estimation of the parameters of statistical distributions used to represent annual peak flow data. The L-moments method is a reliable statistical analytical technique that is increasingly employed in hydrology for this task [2], [11], [20-22]. Precise parameter estimation using L-moments requires solving a set of nonlinear equations, which presents some challenges. The L-moments method is less affected by data length and hence produces more precise results in comparison to the method of moment technique [23].

The benefits of the L-moment technique used in this study are as follows: wide applicability, robustness to outliers and minimal bias [24], [25]. The attributes of L-Moment method make them particularly suitable for regions like Malaysia, where flood events can vary significantly and are influenced by extreme weather. L-moments offer enhanced reliability and stability in estimating distribution parameters, particularly when managing extremely high values, making them crucial for precise measurement of FFA. L-moments can produce stable estimates even with small sample sizes, which is crucial in hydrology, where data for extreme events may be limited [26].

The objective of this study is to apply FFA to Saying River to determine which distribution best fits the annual peak flow data. The selected distribution will then be used to estimate the return period, providing insights into the expected frequency and severity of future floods for policymakers, thereby improving the effectiveness of water management and flood risk assessment.

3. Methodology

3.1 Data

The station selected for this study is the Sungai Sayong River Station, located in Johor, Malaysia. The data is obtained from Department of Irrigation and Drainage, Malaysia. Peak flow data helps identify and quantify extreme flow events, which are critical for assessing flood risk in a specific area. Understanding the frequency and magnitude of peak flows aids in preparing for potential flooding scenarios. Table 1 presents the descriptive statistics of the streamflow characteristics for Sayong River, including the mean, median, standard deviation, variance, kurtosis, and skewness. The dataset was collected over a period of 33 years, starting from 1984.

Table 1. Descriptive Statistics for Sayong River Streamflow

Mean	Median	Standard Deviation	Variance	Kurtosis	Skewness
113.4379	87.99	85.79689	7361.106	9.677445	2.714384

The descriptive statistics for streamflow at the Sayong River station are shown in Table 1. The average flow rate was 113.44 m³/s. The median streamflow was 87.99 m³/s, which is significantly lower than the mean, suggesting the data is highly skewed to the right. A high standard deviation of 85.80 m³/s and indicate considerable variation in streamflow which means there exist extreme value in the data. The positive skewness value of 2.71 indicates that the data distribution is right-skewed. Additionally, a kurtosis score of 9.68 indicates a distribution with heavy tails and a higher frequency of extreme values. Based on the descriptive statistics presented in Table 1, the streamflow at Sayong River station shows evidence of extreme value, suggesting the occurrence of extreme events which are floods.

3.2 GEV Distribution

The Generalized Extreme Value (GEV) distribution is a flexible and extensively employed statistical distribution in hydrology, specifically for representing extreme events like floods or phenomena where only the most extreme values are of significance. The GEV distribution unifies three types of distributions - Gumbel, Fréchet, and Weibull into a single family, distinguished by its adaptability in modelling various extreme events. Its versatility in accommodating various data formats and its capacity to represent both heavy-tailed and bounded distributions make it highly suitable like Malaysia, where the characteristics of flood events can vary greatly among different river basins. The cumulative density function (CDF) of GEV is defined in Eq. 1 and Eq. 2:

$$f(x) = \frac{1}{\alpha}\left[1-k\left(\frac{x-\xi}{\alpha}\right)\right]^{\frac{1}{k}-1} \exp\left\{-\left[1-k\left(\frac{x-\xi}{\alpha}\right)\right]^{\frac{1}{k}}\right\} \tag{1}$$

The quantile function of GEV distribution can be defined as

$$x(F) = \hat{\xi} + \frac{\hat{\alpha}}{\hat{k}}\left\{1-(-\ln(F))^{\hat{k}}\right\} \tag{2}$$

The quantile function is essentially the inverse of the CDF (Cumulative Density Function). While the CDF gives the probability of a variable being below a certain threshold x ,the quantile function (also called the percent-point function) tells us what value of x corresponds to a specific cumulative probability. The definition to estimate the parameter $\hat{\xi},\hat{\alpha},\hat{k}$ definition from Hosking *et al.* [27]. The parameters $\hat{\xi},\hat{\alpha}$ and $\hat{k}$ are estimated according to the definitions provided by Hosking *et al.* [27]. The definition of $\hat{\xi},\hat{\alpha}$ and $\hat{k}$ for GEV distribution are provided in Eq. 3 to Eq. 5:

$$\hat{k} = 7.85890c + 2.9554c^2 \tag{3}$$

where $c = \frac{2}{3+t_3} - \frac{\ln 2}{\ln 3}$

$$\hat{\alpha} = \frac{l_2}{\Gamma(\hat{k})(1-2^{\hat{k}})} \tag{4}$$

$$\hat{\xi} = l_1 - \frac{\hat{\alpha}}{\hat{k}} + \hat{\alpha}\Gamma(\hat{k}) \tag{5}$$

3.3 GLO Distribution

Generalized Logistic (GLO) distribution is used to model the distribution of extreme values, such as high annual maximum flood flows. It is especially effective in scenarios where the tails of the distribution (representing rare and extreme events) need to be accurately represented. This distribution can help predict the likelihood of extreme floods based on historical data.

The probability density function (PDF) of GLO distribution is given by

$$f(x) = \frac{1}{\alpha}\left\{1-k\left(\frac{x-\xi}{\alpha}\right)\right\}^{\frac{1}{k}-1}\left[1+\left\{1-k\left(\frac{x-\xi}{\alpha}\right)\right\}^{\frac{1}{k}}\right]^{-2} \tag{6}$$

The quantile function of GLO distribution can be written as:

$$x(F) = \hat{\xi} + \frac{\hat{\alpha}}{\hat{k}}\left[1-\left\{\frac{(1-F)}{F}\right\}^{\hat{k}}\right] \tag{7}$$

The definition to estimate the parameter $\hat{\xi}, \hat{\alpha}, \hat{k}$ definition from Hosking *et al.* [27]. The parameters $\hat{\xi}, \hat{\alpha}$ and $\hat{k}$ are estimated according to the definitions provided by Hosking *et al.* [27]. The definition of $\hat{\xi}, \hat{\alpha}$ and $\hat{k}$ for GLO distribution are provided in Eq. 8 to Eq. 10:

$$\hat{k} = -t_3 \tag{8}$$

$$\hat{\alpha} = \frac{l_2}{\Gamma(\hat{k})\left[\Gamma(1-\hat{k}) - \Gamma(2-\hat{k})\right]} \tag{9}$$

$$\hat{\varepsilon} = l_1 - \frac{\hat{\alpha}}{\hat{k}} + \hat{\alpha}\Gamma(\hat{k})\Gamma(1-\hat{k}) \tag{10}$$

3.4 Parameter estimation using L-Moment

The L-moment methodology is a statistical technique used for estimating the parameters of probability distributions, particularly in hydrology and environmental sciences. L-moments are analogous to conventional moments (like mean and variance) but offer some advantages, especially when dealing with skewed data or outliers. L-moments are linear combinations of order statistics, which are the sorted values of a sample. Unlike conventional moments, L-moments are less influenced by extreme values or outliers, making them more robust for skewed data. The unbiased sample estimator of the L-Moment method defined by Landwehr *et al.* [28] is:

$$b_r = \frac{1}{n}\binom{n-1}{r}^{-1}\sum_{i=r+1}^{n}\binom{i-1}{r}x_{i:n} \quad r = 0, 1, 2, \ldots \tag{11}$$

The first four L-moments sample estimates can be written as:

$$l_1 = b_0 \tag{12}$$

$$l_2 = 2b_1 - b_0 \tag{13}$$

$$l_3 = 6b_2 - 6b_1 + b_0 \tag{14}$$

$$l_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \tag{15}$$

The L-moments ratio samples are defined as:

$$t_2 = \frac{l_2}{l_1} \tag{16}$$

$$t_3 = \frac{l_3}{l_2} \tag{17}$$

$$t_4 = \frac{l_4}{l_2} \tag{18}$$

t_2 refer to coefficient of variations, t_3 refer to coefficient of skewness and t_4 refer to kurtosis.

3.5 Prediction Error Metrics

An essential component of FFA is choosing a suitable statistical distribution that accurately represents the observed data. Each distribution provides distinct characteristics extreme events and selecting the most appropriate one can greatly influence the reliability of the estimated flood event. In this study three different metrices implemented to determine the best fitted candidate distribution (GEV and GLO) distribution. Most used metrics for evaluating model performance are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The definition for MAPE, MAE, and RMSE is given in the series of equations below Eq.19 to Eq.21, respectively.

$$MAPE = \left(\frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100\% \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2} \tag{20}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right| \tag{21}$$

where y_i is the observed flows, $\hat{y}_i$ is the predicted flows and n is the number of flow series that have been model.

4. Results and Discussion

FFA is a fundamental tool in hydrological, providing insights into the magnitude and frequency of flood events. These analyses are crucial for guiding water resource management and flood mitigation strategies. In this study, the yearly maximum streamflow data, spanning 33 years, were fitted to the GEV and GLO distributions for modelling extreme flood. This data allows for accurate flood frequency analysis and helps design resilient infrastructure. The parameters of GLO and GEV are estimated using the L-Moment method. The parameters of both distributions were estimated using the L-Moment method. The process involves calculating the first four unbiased sample estimators using Eq.11. The value of first four of unbiased sample estimator are:

$$b_0 = 111.4379$$
$$b_1 = 76.5969$$
$$b_2 = 60.1362$$
$$b_3 = 50.5743$$

Once the first four unbiased sample estimators have been obtained, the first four L-moment sample estimates can be calculated by using Eq. 12 to Eq. 15. The values for the first four L-Moment are:

$l_1 = 113.4379$
$l_2 = 39.7559$
$l_3 = 14.6739$
$l_4 = 13.1242$

Using Eq.16 to Eq. 18, L-Moment ratios (t_2, t_3, t_4) can be obtained. The values for the L-moment ratios are:

$t_2 = 0.3505$
$t_3 = 0.3691$
$t_4 = 0.3301$

Using the L-Moment ratios values, by implementing a methodology by Hosking *et al.* [27], the parameter for GEV and GLO can be estimated. The estimated parameters for GEV and GLO distribution.

Table 2. Estimated Parameters using L-Moments for GEV and GLO

Distribution	Parameters		
GEV	$k = -0.289$	$u = 74.121$	$\alpha = 40.439$
GLO	$k = -0.37$	$\varepsilon = 90.872$	$\alpha = 31.427$

Table 2 shown the estimated parameter for the GEV and GLO distributions using L-Moment. The parameters for GEV distribution are $k = -0.289$, $u = 74.121$ and $\alpha = 40.439$. The parameters value for GLO distribution are $k = -0.37$, $\varepsilon = 90.872$ and $\alpha = 31.427$. To determine the most suitable candidate distribution for extreme flood events at Sayong River station, three different metrices are used namely RMSE, MAE and MAPE. Evaluating these measures enables the identification of the distribution that best represents the extreme flood behaviour. A summary of the RMSE, MAE, and MAPE results for the data from Sayong River is presented in Table 3.

Table 3. RMSE, MAE and MAPE at Sayong River Station

Distribution	RMSE		MAE		MAPE	
	Value	Rank	Value	Rank	Value	Rank
GLO	17.7369	1	8.6608	1	11.83%	1
GEV	17.8034	2	8.7957	2	12.98%	2

A thorough assessment of the GLO and GEV distributions, as shown in Table 3, indicates that the GLO distribution offers a superior fit for extreme flood events at Sayong River Station. The GLO distribution exhibits a lower RMSE of 17.7369 in contrast to the GEV 17.8034, indicating that the GLO distribution often yields smaller prediction errors. In terms of MAE value, the GLO distribution also produces lower MAE value which is 8.6608 meanwhile for GEV distribution is 8.7957. The MAPE value for GLO distribution is 11.83% lower than MAPE value for GEV value which is 12.98%. These results indicate that the GLO distribution performs better than the GEV distribution in all assessed metrics. Thus, GLO distribution is selected to represent Sayong river peak streamflow data.

The GLO distribution will be used to estimate the flood occurrence at Sayong river station. A precise estimation of quantiles from the GLO distribution is essential in flood event analysis, as it provides valuable insights into the likelihood of various streamflow levels based on their return periods. Quantile estimates for extreme flood events at Sayong River Station, computed for return periods of 10, 50, and 100 years. The streamflow level is expected to be exceeded once every ten years, as indicated by the 10-year return period projection. This is crucial for strategic long-term planning and infrastructure development, as the 50-year return period suggests a more intense flood event with a 2% likelihood of surpassing projected levels annually. Critical safety planning and design are conducted using the 100-year return period, which is equivalent to a flood occurrence with a 1% annual probability. The return periods for 10, 50, and 100 years are Shown in Table 4.

Table 4. Estimation of T=10,50 and 100 years

T	10	50	100
Q_T	197.3153 m³/s	363.8308 m³/s	469.9711 m³/s

Table 4 presents the quantile estimated for the Sayong River Station for return periods of 10, 50, and 100 years. The 10-year return period estimate of 197.3153 m³/s indicate that the streamflow level is projected to be surpassed on average once every ten years. This value denotes the extent of a very common yet substantial flood occurrence. For the 50-year return period, the calculated quantile of 363.8308 m³/s suggests a more severe flood occurrence with a 2% probability of being surpassed in any given year. An estimated for 100-year return period quantile of 469.9711 m³/s corresponds to a streamflow level that has a 1% probability of being exceeded in any given year. These return period information at Sayong River is crucial for efficient water management and flood mitigation projects.

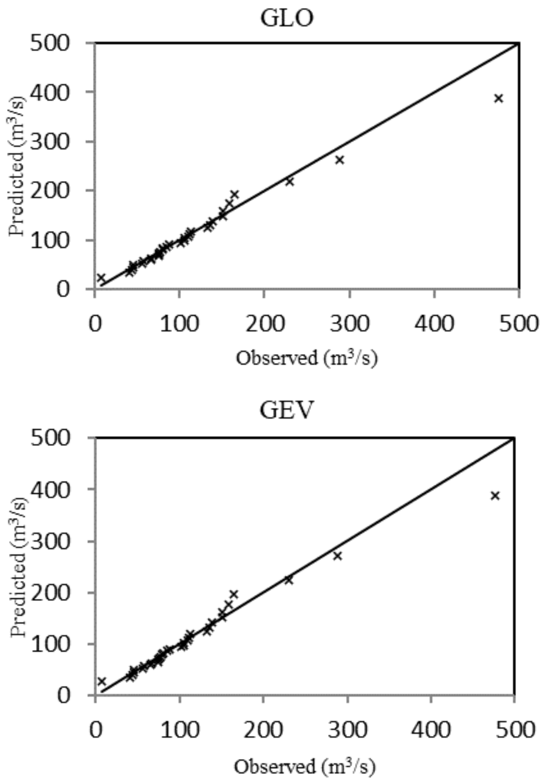

Figure 1. Observed vs. Estimated flood peak value at Sayong river station for GEV and GLO distribution.

5. Conclusion

This study implements FFA to determine the flood occurrences at Sayong River Station through the implementation of GEV and GLO distributions. L moments are used to estimate the parameter of distribution. Then, the parameters for GEV and GLO distributions are utilized to estimate flood quantiles with various return periods. The return periods selected in this study are 10, 50 and 100 years. The results indicate that the GLO distribution fits the peak streamflow data in comparison to the GEV distribution in terms of three different metrices (RMSE, MAE and MAPE). Specifically, the quantile estimates obtained for the 10-year, 50-year, and 100-year return periods were 197.3153 m³/s, 363.8308 m³/s, and 469.9711 m³/s, respectively. Policymakers can use the quantile estimate result from this study for water resource planning at the Sayong River station.

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Conflict of Interest
The authors declare there is no conflict of interest in the subject matter or materials discussed in this manuscript.

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