Applied Mathematics and Computational Intelligence
Volume 15, No. 1, 2026 [87-101]

Comparative Analysis of Extreme Value Distributions for Flood Risk Assessment in Kelantan Rivers using L-Moments

Sheril Haiza Shah Izan[1], Basri Badyalina[2*], Nur Hanida Othman[3], Fatin Farazh Ya'acob[4]

[1, 3]Faculty of Computer and Mathematical Science, Universiti Teknologi MARA (UiTM)Cawangan Negeri Sembilan, Kampus Seremban, 70300 Seremban, Negeri Sembilan, Malaysia.
[2]Faculty of Computer and Mathematical Science, Universiti Teknologi MARA Cawangan Johor, Kampus Segamat, 85000 Johor, Malaysia
[4]Faculty of Business and Management, Universiti Teknologi MARA Cawangan Johor, Kampus Segamat, 85000 Johor, Malaysia

[*] Corresponding author: basribdy@uitm.edu.my

Received: 26 May 2025
Revised: 15 August 2025
Accepted: 21 August 2025

ABSTRACT

Floods are a recurring natural disaster in Kelantan, Malaysia, posing severe risks to communities and infrastructure. This study presents a comparative flood frequency analysis (FFA) using the L-moment method at the Rantau Panjang station along the Golok River to determine the most suitable extreme value distribution for modeling peak flow data. Three distributions were analyzed: the Three-Parameter Log-Normal (LN3), Generalized Logistic (GLO), and Generalized Pareto (GPA). The research evaluated each model based on statistical performance metrics, L-moment ratio diagrams, and goodness-of-fit tests (Kolmogorov-Smirnov and Anderson-Darling). The GLO distribution emerged as the most accurate, yielding the lowest error values and highest R^2, and closely aligned with observed data in the L-moment diagram. Its superior performance in estimating return periods and flood magnitudes confirms its reliability for risk assessment in flood-prone regions. This study demonstrates the efficacy of L-moments in enhancing hydrological modeling, offering vital insights for disaster preparedness and water resource management in Kelantan.

Keywords: Extreme Value Distributions, Flood Frequency Analysis, Flood Risk Assessment, Hydrology, L-Moments, Return Period

1 INTRODUCTION

Kelantan, located in northeastern Peninsular Malaysia, is an agrarian state known for its paddy fields and fishing villages. However, the region faces recurring natural disasters, particularly annual floods. It is caused by several factors like heavy rainfall, high tidal waves, drainage obstruction, shallow streams, and land use change [1, 2]. The devastating impacts of floods in Kelantan include large-scale displacement of citizens to temporary evacuation camps (PPS), large-scale destruction of houses and agricultural lands, and disruption of basic services like electricity, water supply, and healthcare. Against such adversities, flood research is necessary to understand and minimize the effect on vulnerable societies. In this research, Flood Frequency Analysis (FFA) using the L-moments technique is applied in order to determine the most suitable extreme value distribution of the Three-Parameter Log-Normal (LN3), Generalized Logistic (GLO), and Generalized Pareto (GPA). The Kelantan River basin suffers from regular large floods causing widespread loss of life, destruction of properties, and loss of infrastructure such as in the case of 2016/2017 season, which incurred over RM 33 million in economic losses [3]. This study solves this problem through L-moments and performance measures to improve prediction accuracy, supporting mitigation and risk management of disasters. This study will solve three major goals. First, it seeks to establish the best extreme value distribution, either Three-Parameter Log-Normal (LN3), Generalized Logistic (GLO), or Generalized Pareto (GPA), to efficiently estimate flood risk in Kelantan. Second, the study approximates the parameters of these distributions in order to enhance flood modelling for Kelantan River. Third, the research estimates return periods for various magnitudes of floods, which is critical information regarding prospective flood hazards and planning long-term disaster preparedness strategies. This research enhances flood risk assessment approaches for the Kelantan River, a region with recurrent and intense flooding. From a comparison of the LN3, GLO, and GPA distributions using L-moments, the study provides critical data on the model that best characterizes the behaviour of floods in the basin. The findings will improve the accuracy of flood predictions, enabling policymakers and disaster management stakeholders to develop more effective mitigation measures. Due to the limitation of time, this study focuses on a single hydrological station (Rantau Panjang) of the Golok River, Kelantan focuses only on three distributions (LN3, GLO, GPA). A broader study with additional stations and distributions may further contribute to the findings.

Flood Frequency Analysis is a cornerstone of hydrology and flood risk management, enabling the prediction of return periods and sizes of flood events [4-6]. Such predictions form the basis for hydrological planning, guiding the construction of infrastructure and flood protection measures. In flood-risk zones, FFA supports river basin planning, climate change adaptation and the creation of resilient drainage systems, mitigating the impact of flooding on society and the environment [7-9]. The most widely used distributions utilized in FFA for estimation of annual peak flow of river stations in Malaysia include Generalized Pareto distribution (GPA), Generalized Extreme Value distribution (GEV), Generalized Logistic distribution (GLO), Pearson Type-3 distribution (P3), and Three-Parameter Log-Normal (LN3) [7, 10-12].

L-moments, as introduced by Hosking [13], have significant advantages over conventional moments in flood modelling since they are outlier-resistant and extreme value resistant. L-moments are linear combinations of order statistics, which reduces the effect of extreme events on the analysis. This makes L-moments provide more robust estimates of distribution parameters even if the data include outliers or are non-normal, as is the case with flood-prone areas. These case studies such as the Segamat River [14] and Triang River in Pahang [15] also illustrated the better performance of L-moments, with better identification of distributions like LN3 and GEV, leading to improved flood prediction and risk management strategies. The three-parameter log-normal (LN3) distribution is a generalized and popular statistical model for the analysis of hydrological data, particularly in flood magnitude and frequency study [16]. Created by Wallis [17] in his regional hydrology and flood frequency analysis study, the LN3 distribution has been found to be applicable in flood-prone regions such as Kelantan and Terengganu. Ng et al. [18] employed LN3 in analysing flood frequency of yearly peak streamflow of the Kelantan River and was discovered to be particularly suitable because of the hydrologic variability of the region. Deraman et al. [19] also identified LN3 as the most appropriate in analysing the flood frequency of Air Putih, Kemaman, Terengganu.

The Generalized Logistic (GLO) distribution is a powerful and flexible statistical method of extreme flood event analysis and hence an effective part of hydrological modelling and flood risk analysis. The GLO distribution was initially developed and implemented in hydrology by Singh [20], and subsequently applied across the world for its ability to model a wide range of skewness and tail behaviours and thereby conduct efficient streamflow and flood frequency data analysis. Salarijazi et al. [21] demonstrated the usefulness of the GLO in agricultural water management through the simulation of streamflow and water quality data sets. Similarly, Yang et al. [22] and Zhou et al. [23] revealed the distribution's accuracy for predicting hydrologic events such as debris flows and predicting river system variables. Malaysian flood research, Bakri et al. [24] and Ilias et al. [25], validate the better fit of the GLO distribution over other models such as the Generalized Extreme Value (GEV) and Generalized Pareto (GPA) distributions in flood frequency analysis. The Generalized Pareto (GPA) distribution is a leader in extreme value analysis, most notably in flood event modelling and analysis. Formulated by Pickands [26] in the context of extreme value theory, GPA is specialized in the modelling of the exceedance over a threshold. It is thus particularly adapted to the study of the tail distributions of data sets, where the extreme events are located. Pickand's seminal work placed GPA as a reference in hydrology, where GPA in routinely employed to assess the streamflow events. A number of studies have also determined the suitability and applicability of GPA in flood frequency analysis (FFA) [27]. Hassim et al. [28] applied the GPA to the Kelantan River Basin and concluded that it outperformed other distributions for FFA, showcasing its suitability for modelling flood-prone regions. Similarly, Badyalina et al. [29] highlighted the GPA's efficacy in modelling annual maximum flows in the Bekok River, while Hamzah et al. [30] identified the GPA as the best fit for the partial duration series at Kajang station.

2 METHODOLOGY

2.1 Study Area

Kelantan is one of the largest states in Peninsular Malaysia which consist often districts and the state capital of Kelantan is Kota Bharu. Districts such as Pasir Mas, Machang, Kota Bharu and Kuala Krai are the most affected annually by flooding year by year. The river Kelantan catchment is located in north-eastern of Peninsular Malaysia between the latitudes of 4°30′N and 6°15′N and longitudes 101°00′E and 102°45′E. It is one of the major rivers in Malaysia that frequently faces flooding events. The river spans 248 km, with a drainage area of 13,100 km^2 and an average width of 180 to 300 m. The extreme streamflow data are collected from the Department of Irrigation and Drainage Malaysia (DIDM), which is a government organization of Malaysia dealing with water resources. The period of the data spans from 1962 to 2022, which is 60 years. This research focuses on one station along the Golok River, Rantau Panjang (Station ID: 6019411) as shown in Figure 1 and Figure 2.

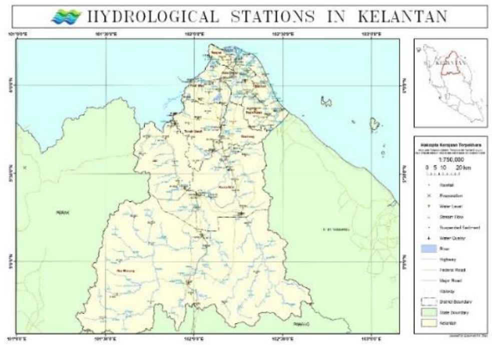

Figure 1 : Kelantan's River

Figure 2 : Rantau Panjang Map

2.2 L-Moment

The L-Moment was defined by Hosking [13] as a linear combination of Greenwood et al. [31] probability weighted moments (PWMs). L-Moment are linear functions of PWMs that were introduced by Hosking [13]. L-moment can be interpreted directly as the measure of scale and shape probability distributions, where in this case, they are analogous to conventional moments indicates that L-Moment are more convenient than PWMs [32]. According to Greenwood et al. [31], the L-moment method's unbiased sample estimator is:

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

where $x_{i:n}$ is the sequence data of stream flow, b_r is the PWM and n is the sample size. Therefore, an unbiased sample estimator's first four components are referred as follow:

$$b_0 = \frac{1}{n}\sum_{i=1}^{n} x_{i:n} \tag{2}$$

$$b_1 = \frac{1}{n} \sum_{i=2}^{n} \frac{(i-1)}{(n-1)} x_{i:n} \tag{3}$$

$$b_2 = \frac{1}{n} \sum_{i=3}^{n} \frac{(i-1)(i-2)}{(n-1)(n-2)} x_{i:n} \tag{4}$$

$$b_3 = \frac{1}{n} \sum_{i=4}^{n} \frac{(i-1)(i-2)(i-3)}{(n-1)(n-2)(n-3)} x_{i:n} \tag{5}$$

The sample estimates for the first four L-Moments can be expressed as follows:

$$l_1 = b_0 \tag{6}$$

$$l_2 = 2b_1 - b_0 \tag{7}$$

$$l_3 = 6b_2 - 6b_1 + b_0 \tag{8}$$

$$l_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \tag{9}$$

where (l_1) is the mean of distribution, (l_2) is the measure of scale. (l_3) is the measure of skewness and (l_4) is the measure of kurtosis.

The LMO ratios, which are comparable to convectional moment ratios, can also be obtained using LMO [13]. Therefore, the LMO ratio sample are addressed as follows:

$$t_2 = \frac{l_2}{l_1} \tag{10}$$

$$t_3 = \frac{l_3}{l_2} \tag{11}$$

$$t_4 = \frac{l_4}{l_2} \tag{12}$$

where t_2 is the measure of scale and dispersion, t_3 is the measure of skewness and t_4 is the measure of kurtosis.

Table 1: L-Moment Components

l_1 ***(Mean)***	l_2 ***(Scale)***	l_3 ***(Skewness)***	l_4 ***(Kurtosis)***
392.1244	78.26516	3.522556	18.98375

Table 1 presents the first four components of L-moments, which describe the statistical characteristics of the flood data. The mean (392.1244) represents the central tendency of the data and reflects the average magnitude of flood events. The scale (78.26516) measures the variability of the data around the mean, indicating a moderate to high spread in flood magnitudes. The skewness (3.522556) reveals a strong positive skew, showing that the data is heavily skewed toward lower magnitudes. This suggests that high-magnitude floods occur less frequently but can still have a significant impact. Finally, the kurtosis (18.98375) indicates heavy tails in the distribution, implying that extreme flood events, though rare, are possible and could be more severe than expected under a normal distribution.

Table 2: Estimated Distribution Parameter using the L-Moment Technique

Dist	Cumulative Density function	Parameter Estimation
LN3	$x(F)=\alpha+e^{\xi+uk};u=\Phi^{-1}[1-\Phi]$	$\hat{k}=-0.001005+0.997386z+0.001027z^2-0.005853z^3-0.000154z^4+0.000141z^5$ where $z=\sqrt{\frac{8}{3}}\Phi^{-1}\left[\frac{1+t_3}{2}\right]$, Φ^{-1} is inverse CDF of Normal Distribution. $\alpha=\ln(l_2)-\ln\left(2S_1(k)-e^{\frac{k^2}{2}}\right)$; $\xi=l_1-e^{\alpha+\frac{k^2}{2}}$
GLO	$x(F)=\left[1+\left\{1-k\left(\frac{x-\xi}{\alpha}\right)\right\}^{\frac{1}{k}}\right]^{-1}$	$\hat{k}=-t_3$; $\hat{\alpha}=\frac{l_2}{\Gamma(\hat{k})\left[\Gamma(1-\hat{k})-\Gamma(2-\hat{k})\right]}$ $\hat{\xi}=l_1-\frac{\hat{\alpha}}{\hat{k}}+\hat{\alpha}\Gamma(\hat{k})\Gamma(1-\hat{k})$
GPA	$x(F)=\hat{\xi}+\frac{\hat{\alpha}}{\hat{k}}\left[1-\left\{\frac{(1-F)}{F}\right\}^{\hat{k}}\right]$	$\hat{k}=\frac{1-3t_3}{1+t_3}$; $\hat{\alpha}=l_2(\hat{k}+1)(\hat{k}+2)$ $\hat{\xi}=l_1-\frac{\hat{\alpha}}{\hat{k}}+\frac{\hat{\alpha}}{\hat{k}(\hat{k}+1)}$

Table 2 provides an overview of the cumulative distribution function (CDF) and the estimated parameters for each distribution. In this context, $x(F)$ denotes the estimated discharge corresponding to a specific non-exceedance probability F, which is linked to a return period T through the relationship $F=1-1/T$. The symbols ξ, α, and k refer to the estimated location, scale, and shape parameters, respectively, for each distribution model.

2.3 Accuracy Measure Performance

This section is organized into three sub-sections: performance evaluation using accuracy measures, analysis through the L-moment Ratio Diagram (LMR), and application of goodness-of-fit (GOF) tests to determine the most suitable distribution for the Rantau Panjang site.

2.4 L-Moment Ratio Diagram (LMR)

Hosking and Wallis [13] recommend the L-Moment Ratio Diagram (LMRD) as an effective tool for selecting a suitable distribution that accurately represents the streamflow series of the catchment. A ratio diagram can be constructed with a simple explicit expression for t_4 in terms of t_3 for the selected probability distribution. The construction of polynomial approximations has taken the form of:

$$t_4 = A_0 + A_1 t_3 + A_2 (t_3)^2 + A_3 (t_3)^3 + A_4 (t_3)^4 + A_5 (t_3)^5 + A_6 (t_3)^6 + A_7 (t_3)^7 + A_8 (t_3)^8 \tag{13}$$

The parameters A_k for the LN3, GLO, and GPA distributions are estimated using L-Moments. To quantify the separation between two points, the Euclidean Distance is commonly applied. This distance commonly used to determine the shortest path between two points, particularly in applications like LMRD. According to Krislock & Wolkowicz [33] the formula for calculating this distance is given by:

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{14}$$

2.4.1 Goodness of Fit Test

Several goodness of fit tests is frequently employed in this research area. However, compared to the other tests in identifying a suitable model, this study primarily focuses on the higher rejection power of the Anderson-Darling (AD) Test and Kolmogorov-Smirnov (K-S) Test [34]. In the field of hydrology, the K-S test is commonly used to evaluate the suitability of statistical distributions. Hypothesis testing was conducted to determine whether the data followed specific distributions, using both the K-S and AD tests.

H_0: The data follow the specified distribution.
H_1: The data does not follow the specified distribution.
If p-values < α , reject H_0

The equation of K-S test statistic is as follows [32]:

$$D_{N_j} = max\left|F_N(x) - F_0(x)\right| \tag{15}$$

where N_j stands for the cumulative number of sample events at class limit *j*, and the values of $F_N(x)$ are estimated. Values of $F_N(x)$, where k is the number of class intervals, *1/k*, *2/k*, ..., etc. The Anderson-Darling (AD) test is a statistical approach to detecting departures from normality in sample distributions. Especially, the AD test converges extremely quickly to its asymptotic distribution and consequently becomes even more effective for goodness-of-fit testing [35]. The AD test formula is presented by [32]:

$$AD = -n - \frac{1}{n}\sum_{i=1}^{n}\left[(2i-1)\ln\left(F\left(X_{(i)}\right)\right) + \ln\left(1 - F\left(X_{(n-i+1)}\right)\right)\right] \tag{16}$$

2.4.2 Performance Measurement

There are five accuracy measurement used in this research, which include the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), the Root Mean Square Error (RMSE), the Root Mean Square Percentage Error (RMSPE) and the Coefficient of Determination (R^2) [36]. The definition of each accuracy measurement is defined in Eq. 17 to Eq. 21.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|F(y_i) - F(\hat{y}_i)\right| \tag{17}$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{F(y_i) - F(\hat{y}_i)}{F(y_i)}\right|\right)\times 100\% \tag{18}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(F(y_i) - F(\hat{y}_i)\right)^2} \tag{19}$$

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{F(y_i) - F(\hat{y}_i)}{F(y_i)}\right)^2}\times 100\% \tag{20}$$

$$R^2 = \frac{\sum_{i=1}^{n} F(\hat{y}_i) - F(\bar{y}_i)^2}{\sum_{i=1}^{n} F(\hat{y}_i) - F(\bar{y}_i)^2 + \sum_{i=1}^{n} F(y_i) - F(\hat{y}_i)^2} \tag{21}$$

where n stands for the number of observations, $F(y_i)$ represents the actual values and $F(\hat{y}_i)$ is the predicted value for the i-th observations, and $F(\bar{y}_i)$ represents the mean of the actual values. MAE and RMSE determine how closely the predictions match the observations by comparing the best model based on the relatively small MAE and RMSE values. The MAPE indicates how effectively a model can make prediction. MAPE expressed the error as a percentage, which allowing researchers to easily compare the predictive performance of different models. Generally, the model with the lowest MAPE is preferred for making predictions. The RMSPE, as a percentage-based variant of RMSE, impacts flood risk model selection by emphasizing relative errors in percentage terms. The R^2 measures the degree to which the actual data may be fitted by the theoretical estimated value derived from the distribution. A higher value of R^2 shows that the model fits the data better.

3 RESULTS AND DISCUSSION

The peak river flows are of great significance in flood engineering, the effectiveness of drainage infrastructure, and the monitoring of flood mitigation structures. Table 1 presents the descriptive statistics of the observed peak flow data at Rantau Panjang gauging station. The peak flow values, in cubic meters per second, are extremely positively skewed, indicating that the data is dominated by biased towards the smaller magnitudes. This indicates that floods of large magnitude are less frequent but can continue to be significant. In this study, the yearly maximum series of daily streamflow at Rantau Panjang, Kelantan, is marked by three distributions, LN3, GLO and GPA. These distributions were selected for their suitability in modelling annual maximum flow data within the

Malaysian context. To evaluate the goodness of fit, the Gringorton plotting position formula is applied, and the observed flood data is compared to the cumulative distribution functions (CDFs) of the candidate distributions, as shown in Figure 3.

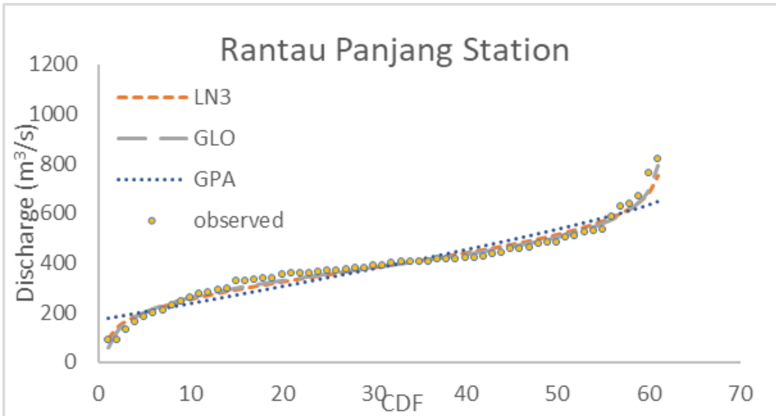

Figure 3 : CDF plot for the Rantau Panjang Annual Peak Flow and the Candidate Distribution

The cumulative distribution function (CDF) plot for Rantau Panjang Station, the GLO distribution shows the closest alignment with the observed data across most parts of the graph, particularly in the right tail, which is critical for flood risk analysis. While all three candidate distributions (LN3, GLO, and GPA) represent the central portion of the data reasonably well, the GLO distribution clearly provides the best fit overall. It closely follows the observed data points throughout the entire range, especially in the upper extremes, which are essential for predicting severe flood events. In contrast, the GPA distribution underestimates peak discharges in the right tail, and LN3 slightly deviates in the upper extremes. Therefore, the GLO distribution proves to be the most suitable model for flood frequency analysis at this station, as confirmed by its graphical performance using the Gringorton plotting position.

Table 3 : Estimated Distribution Parameters using L-Moment Methods

	Parameters		
Distribution	α	ξ	k
LN3	0.09215917	-1114.178	7.313167
GLO	78.00463159	386.33584348	-0.04500797
GPA	404.497045	170.812300	0.827722

Table 3 presents the estimated parameters for LN3, GLO, and GPA distributions using the L-moment method. Among the three, GLO shows the highest location parameter, indicating higher average flood magnitudes. Its negative shape parameter suggests a bounded tail, making it suitable for modeling moderate flood events. Although LN3 and GPA capture extreme values with their heavy-tailed characteristics, GLO provides the most balanced fit to the observed data, making it the best distribution for flood modeling at the Rantau Panjang site. Next, this study identifies the optimal distribution using three key evaluation approaches: accuracy performance measures, GOF tests, and the L-moment diagram. Table 4 shows the performance measurement for the distributions:

Table 4 : Test Performance Measurement for Distributions

Distribution	LN3	GLO	GPA
MAE	20.15625	**15.59828**	37.08699
MAPE	0.06123042	**0.05192106**	0.1222028
RMSE	24.61905	**18.9044**	46.29384
RMSPE	**0.0775226**	0.09035428	0.1423933
R^2	0.9675248	**0.9811633**	0.883236

Based on the performance metrics in Table 4, the GLO distribution is identified as the best model for flood data at this station. It records the lowest MAE (15.59828), MAPE (0.05192106), and RMSE (18.9044), indicating high accuracy and minimal prediction error. Although its RMSPE (0.09035428) is not the lowest, it still outperforms GPA significantly. Additionally, GLO achieves the highest R^2 value (0.9811633), showing it explains the most variance in the data. Overall, GLO consistently delivers the best results across key metrics, making it the most reliable distribution for this analysis.

Table 5 : P-value of GOF Test for each Distributions

Distribution	LN3	GLO	GPA
AD	0.5938	**0.7499**	9.836e-06
K-S	0.5001	**0.6426**	5.505e-10

Table 5 shows the p-values from the AD and K-S goodness-of-fit tests for LN3, GLO, and GPA distributions. GLO has the highest p-values (AD = 0.7499, K-S = 0.6426), indicating the best fit to the observed flood data. LN3 also fits reasonably well, while GPA performs poorly with very low p-values. These results confirm that GLO is the most suitable and stable distribution to use in simulating flood magnitudes in this study.

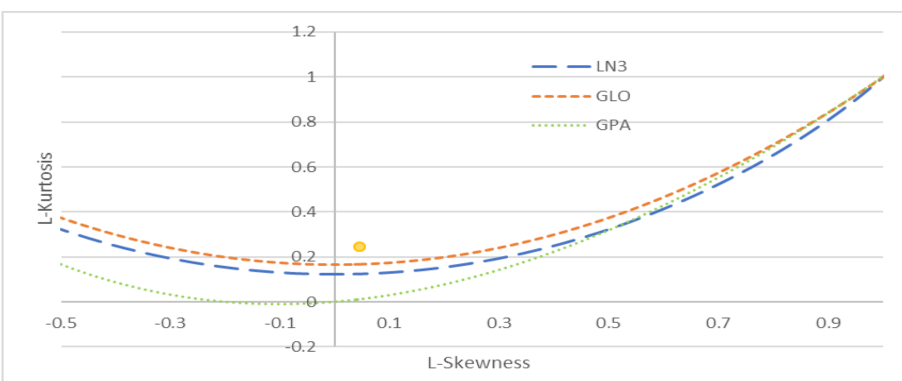

Figure 4 : L-Moment Ratio Diagram

Figure 4 is the L-Moment Ratio Diagram (LMRD) that plots the relationship between observed data's and theoretical distributions' L-Skewness (t^3) and L-Kurtosis (t^4). The observed data point with the L-Kurtosis value of 0.2425568 is located closest to the GLO distribution proves that the

GLO distribution best describes the statistical characteristics of observed flood data. In comparison, the LN3 and GPA curves are farther from the observed point, indicating these distributions are less appropriate in representing the data more accurately. This also confirms the choice of GLO as the most appropriate model to employ for flood frequency analysis in the study area. To assess goodness of fit between the observed L-moment ratio valued and the fitted distributions, the Euclidean distance approach is employed. This plot calculated the difference between the empirical point and the theoretical value of both distributions so that we can compare directly. The closer the Euclidean distance, the better the fit, and thus one can determine which distribution best fit the flood data.

Table 6 : Euclidean Distance for Each Distributions

Distribution	Euclidean Distance
LN3	0.1182
GLO	**0.0742**
GPA	0.2315

Table 6 presents the Euclidean distances between the observed and predicted L-moment ratio values for the LN3, GLO, and GPA distributions. Among these, the shortest distance (0.0742) is for the GLO distributions. Among these, the shortest distance (0.0742) is for the GLO distribution, denoting the closest fit to the observed data. This reinforces GLO as the most appropriate model for flood frequency analysis at the study location, and thus it is the most appropriate model to utilize in making accurate flood predictions and risk evaluation.

To achieve a reasonable conclusion, this research adopts a rank scoring system for identifying the best-fitting distribution that suits the target area. Each distribution is given a score based on the goodness-of-fit to the observed data, from 3 for the best model to 1 for the worst-fitting.

Table 7 : Rank Score for Distributions

Distribution	LN3	GLO	GPA
AD	2	**3**	1
K-S	2	**3**	1
MAE	2	**3**	1
MAPE	2	**3**	1
RMSE	2	**3**	1
RMSPE	**3**	2	1
R^2	2	**3**	1
Euclidean Distance	2	**3**	1
Total Score	17	**23**	8

Table 7 summarizes the ranking of LN3, GLO, and GPA distributions across seven performance measures and Euclidean distance of LMR. GLO performs the best with the total score of 23, ranking first in seven out of eight criteria, i.e., GOF tests, the most critical accuracy measures and LMR. LN3 ranks second with 17 points, being the best for the RMSPE measure. GPA ranks the worst for all the measures with just 8 points. In total, GLO is shown to be the most appropriate distribution for site modelling as it consistently performed at the highest level.

Table 8 : Quantile Estimates Based on Return Periods

Return Period	Probability	Estimated Flood Discharge (m^3/s)		
(Years)	(p)	LN3	**GLO**	GPA
2	0.50	385.7412	**386.3358**	384.1642
10	0.90	573.7774	**566.4907**	586.8371
50	0.98	698.2784	**718.1267**	640.3235
100	0.99	744.3886	**784.5353**	648.6953

Finally, Table 8 indicates that the most accurate flood discharge estimated are given by GLO distribution, particularly for extended return periods. It gives more realistic and greater values of extreme events with a maximum discharge of 784.5353 m^3/s at the 100-year return period. This positions GLO as the best-suited model to use in this study for flood frequency analysis for accurate risk estimation and effective long-term flood management and infrastructure planning.

4 CONCLUSION

Flood Frequency Analysis (FFA) remains a vital tool in hydrologic engineering for flood hazard comprehension and management. This study focused on identifying the most suitable three-parameter probability distribution to represent the annual maximum flow at Rantau Panjang river station. Using L-moment procedure for parameter estimation, the rival distributions, GLO, GPA, and LN3 were contrasted using goodness-of-fit tests, L-moment ratio diagram, and numerical performance measures. Among the distributions examined, the GLO distribution ranked best in all the evaluation measures used, such as statistical accuracy and reliability in extreme event prediction. The GLO distribution is thus concluded to be the most suitable model for FFA in the Rantau Panjang station. This distribution can serve as an efficient tool for future regional studies in Kelantan hydrological settings.

ACKNOWLEDGEMENT

The authors acknowledged the financial support from the Ministry of Higher Education Malaysia through Fundamental Research Grant Scheme FRGS-EC/1/2024/STG06/UITM/02/12.

REFERENCES

[1] B. Merz, G. Blöschl, S. Vorogushyn, F. Dottori, J. C. Aerts, P. Bates, M. Bertola, M. Kemter, H. Kreibich, and U. Lall, "Causes, impacts and patterns of disastrous river floods," *Nature Reviews Earth & Environment,* vol. 2, no. 9, pp. 592-609, 2021.

[2] N. D. Zamani, B. Badyalina, M. Z. H. B. Abd Jalal, R. M. Khalid, F. F. Ya'acob, and K. L. Chang, "Assessing flood risk through frequency analysis at sayong river station," *Mathematical Sciences and Informatics Journal,* vol. 5, no. 2, 2024.

[3] N. Zulkepli, N. Diana, and M. Idris, "Identifying the research of flooding in kelantan, malaysia:

a review," *International Journal of Mechanical Engineering,* vol. 7, no. 4, pp. 974-5823, 2022.

[4] M. Farooq, M. Shafique, and M. S. Khattak, "Flood frequency analysis of river swat using log pearson type 3, generalized extreme value, normal, and gumbel max distribution methods," *Arabian Journal of Geosciences,* vol. 11, pp. 1-10, 2018.

[5] S. Latif and F. Mustafa, "Parametric vine copula construction for flood analysis for Kelantan river basin in Malaysia," *Civil Engineering Journal,* vol. 6, no. 8, pp. 1470-1491, 2020.

[6] B. Badyalina, A. Shabri, and M. F. Marsani, "Streamflow estimation at ungauged basin using modified group method of data handling," *Sains Malaysiana,* vol. 50, no. 9, pp. 2765-2779, 2021.

[7] A. M. Ahmad, N. S. Romali, and S. Sulong, "Flood frequency analysis of annual maximum stream flows for kuantan river basin," in *AIP Conference Proceedings*, 2023, vol. 2688, no. 1: AIP Publishing.

[8] N. Dabire, E. C. Ezin, and A. M. Firmin, "Determination of hydrological flood hazard thresholds and flood frequency analysis: case study of nokoue lake watershed," *Water,* vol. 17, no. 8, p. 1147, 2025.

[9] N. A. M. Jan, A. Shabri, and B. Badyalina, "Selecting probability distribution for regions of peninsular malaysia streamflow," in *AIP Conference Proceedings*, 2016, vol. 1750, no. 1: AIP Publishing.

[10] N. A. Mat Jan, A. Shabri, M. F. Marsani, and B. Badyalina, “TL-moments approach: application of non-stationary gev model in flood frequency analysis,” *Research Square*, Preprint, Version 1, Jul. 2021. doi: 10.21203/rs.3.rs-673867/v1.

[11] N. A. M. Jan, A. Shabri, S. Ismail, B. Badyalina, S. S. Abadan, and N. Yusof, "Three-parameter lognormal distribution: Parametric estimation using L-moment and TL-moment approach," *Jurnal Teknologi (Sciences & Engineering),* vol. 78, no. 6-11, 2016.

[12] B. Badyalina and A. Shabri, "Flood frequency analysis at ungauged site using group method of data handling and canonical correlation analysis," *Modern Applied Science,* vol. 9, no. 6, p. 48, 2015.

[13] J. R. M. Hosking and J. R. Wallis, *Regional Frequency Analysis: An Approach Based on L-Moments*, Cambridge, U.K.: Cambridge Univ. Press, 1997.

[14] B. Badyalina, N. A. Mokhtar, N. A. M. Jan, N. H. Hassim, and H. Yusop, "Flood frequency analysis using L-moment for Segamat river," *Matematika,* pp. 47-62, 2021.

[15] S. Samat, N. Lewis, and N. Othman, "Low Flow Frequency Analysis at Triang River Streamflow Station," in *IOP Conference Series: Earth and Environmental Science*, 2024, vol. 1296, no. 1: IOP Publishing, p. 012017.

[16] J. Ranger, J. T. Kuhn, and T. M. Ortner, "Modeling responses and response times in tests with the hierarchical model and the three-parameter lognormal distribution," *Educational and*

Psychological Measurement, vol. 80, no. 6, pp. 1059-1089, 2020.

[17] J. R. Wallis, "The three-parameter log normal distribution and its application to hydrology," *Water Resources Research,* vol. 1, no. 1, pp. 95-103, 1965, doi: 10.1029/WR001i001p00095.

[18] J. L. Ng, Y. F. Huang, S. K. Tan, J. C. Lee, N. I. F. Md Noh, and S. Y. Thian, "Comparative evaluation of various parameter estimation methods for extreme rainfall in kelantan river basin," *Theoretical and Applied Climatology,* vol. 155, no. 3, pp. 1759-1775, 2024.

[19] W. H. A. W. Deraman, N. J. Abd Mutalib, and N. Z. Mukhtar, "Determination of return period for flood frequency analysis using normal and related distributions," in *Journal of Physics: Conference Series*, 2017, vol. 890, no. 1: IOP Publishing, p. 012162.

[20] V. P. Singh, Entropy-Based Parameter Estimation in Hydrology. Dordrecht, The Netherlands: Springer Science & Business Media, 1998.

[21] M. Salarijazi, I. Ahmadianfar, and Z. M. Yaseen, "Prediction enhancement for surface water sodium adsorption ratio using limited inputs: Implementation of hybridized stacked ensemble model with feature selection algorithm," *Physics and Chemistry of the Earth, Parts a/b/c,* vol. 134, p. 103561, 2024.

[22] L. Yang, Y. Ge, B. Chen, Y. Wu, and R. Fu, "Machine-learning-based prediction modeling for debris flow occurrence: a meta-analysis," *Water,* vol. 16, no. 7, p. 923, 2024.

[23] X. Zhou, Y. Leng, M. Salarijazi, I. Ahmadianfar, and A. A. Farooque, "Development of forecasting of monthly SAR time series in river systems: A multivariate data decomposition-based hybrid approach," *Process Safety and Environmental Protection,* vol. 188, pp. 1355-1375, 2024.

[24] S. N. F. A. Bakri, "At-site and regional frequency analysis of extreme rainfall modelling in peninsular malaysia," *Applied Mathematics and Computational Intelligence (AMCI),* vol. 11, no. 2, pp. 534-549, 2022.

[25] I. S. Che Ilias, W. Z. Wan Zin, and A. A. Jemain, “Regional frequency analysis of extreme precipitation in Peninsular Malaysia,” in Proc. 5th Int. Conf. Computing, Mathematics and Statistics (iCMS 2021), Kuala Lumpur, Malaysia, Aug. 2021, pp. 160–172.

[26] J. Pickands III, "Statistical inference using extreme order statistics," *the Annals of Statistics,* pp. 119-131, 1975.

[27] B. Badyalina, N. A. Mokhtar, N. A. M. Jan, and M. FADHIL, "Hydroclimatic data prediction using a new ensemble group method of data handling coupled with artificial bee colony algorithm," *Sains Malaysiana,* vol. 51, no. 8, pp. 2655-2668, 2022.

[28] N. H. Hassim, B. Badyalina, N. A. Mokhtar, M. Z. H. Abd Jalal, N. D. B. Zamani, L. C. Kerk, A. I. Zainoddin, A. S. A. Fadzil, and N. F. Shaari, "In situ flood frequency analysis used for water resource management in kelantan river basin," *International Journal of Statistics and Probability,* vol. 11, no. 5, 2022.

[29] B. Badyalina, N. A. Mokhtar, F. F. Ya'acob, M. F. Ramli, M. Majid, and N. A. M. Jan, "Flood frequency analysis using l-moments at labis in bekok river station," *Applied Mathematical Sciences,* vol. 16, no. 11, pp. 529-536, 2022.

[30] F. M. Hamzah, H. Tajudin, and O. Jaafar, "A comparative flood frequency analysis of high-flow between annual maximum and partial duration series at sungai langat basin," *Sains Malaysiana,* vol. 50, no. 7, pp. 1843-1856, 2021.

[31] J. A. Greenwood, J. M. Landwehr, N. C. Matalas, and J. R. Wallis, "Probability weighted moments: definition and relation to parameters of several distributions expressable in inverse form," *Water resources research,* vol. 15, no. 5, pp. 1049-1054, 1979.

[32] K. H. Hamed and A. R. Rao, Flood Frequency Analysis. Boca Raton, FL, USA: CRC Press, 2019.

[33] N. Krislock and H. Wolkowicz, "Euclidean distance matrices and applications," in *Handbook on semidefinite, conic and polynomial optimization*: Springer, 2012, pp. 879-914.

[34] J.-H. Heo, H. Shin, W. Nam, J. Om, and C. Jeong, "Approximation of modified anderson–darling test statistics for extreme value distributions with unknown shape parameter," *Journal of Hydrology,* vol. 499, pp. 41-49, 2013.

[35] S. Dey, E. Raheem, S. Mukherjee, and H. K. T. Ng, "Two parameter exponentiated gumbel distribution: properties and estimation with flood data example," *Journal of Statistics and Management Systems,* vol. 20, no. 2, pp. 197-233, 2017.

[36] T. O. Hodson, "Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not," *Geoscientific Model Development Discussions,* vol. 2022, pp. 1-10, 2022.