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In Situ Flood Frequency Analysis Used for Water Resource Management in Kelantan River Basin

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Abstract

One of the most prevalent and traditional uses of statistics in hydrology is flood frequency analysis. The flood can occur practically everywhere and is considered the leading cause of natural disaster death worldwide. This study aims to apply the flood frequency analysis of the Kelantan streamflow site to identify the optimal distribution that best fits the flood frequency data from the goodness-of-fit test (GOF). Five distributions were applied in this study; namely lognormal (LG), generalized extreme value (GEV), generalized Pareto (GP), log-Pearson three (L3) and generalized logistic (GL) distribution. to obtain the parameter estimates. The distribution performance evaluation is then performed utilizing the GOF and efficiency evaluations. The results indicate that the generalized GP distribution is the best possible function for determining the annual peak flow at the Kelantan streamflow site.

Keywords: generalized pareto, L-Moment, Malaysia

1. Introduction

In Malaysia, floods have been the most damaging natural event. This is because it is geographically subject to seasonal monsoon winds, which bring torrential rainfall to the country's north and east coasts (Mabahwi and Nakamura, 2020; Mokhtar et al., 2021; Mokhtar et al., 2021; Badyalina et al., 2022). In Kelantan, floods are considered an annual natural phenomenon and the worst record-setting flood of 2014 was recorded as a 'tsunami-like disaster' (Baharuddin et al., 2015). According to Weng et al. (2016), the flood that badly affected Kelantan in December 2014 was a very severe flood that resulted in flood losses in terms of lives lost, injuries, infrastructure destruction, property damage, crop loss, loss of livelihoods, interruption of routine services, and healthcare costs. Thus, estimating flood frequency is a critical issue, especially in water resource management, because it is used to design hydraulic structures and gives essential information (Badyalina et al., 2016; Jan et al., 2016; Kim and Lee, 2021). In flood frequency analysis, the parameters of distributions are often estimated using the L-moments approach. L-moments were first proposed by Hosking (1990) as a method for estimating distribution parameters using a linear combination of probability-weighted moments (Jan et al., 2016; Kang et al., 2019). According to David and Nagaraja (2004), L-moments are derived from the expectations of order statistics. Hence this may be a factor that is better than conventional moments for describing distribution form (Jan et al., 2018; Asquith, 2007). L-moments are widely used in applied research such as civil engineering, meteorology, and hydrology. L-moments are widely used in applied research such as civil engineering, meteorology, and hydrology. Among the benefits of L-moments include their capacity to work as a linear function of the data, being less prone to sample variability, being more robust to extreme values or outliers in the data and allowing for more confident inferences about the underlying probability distribution from small samples (Anas et al., 2021). This implies that L-moments are less affected by outliers, and the bias of their small sample estimates is kept to a minimum. In addition, because L-moments are linear combinations of order statistics, they have been demonstrated to be more useful in estimating statistical parameters than other methods, such as the method of moments and least squares (Maleki-Nezhad, 2014). This finding is supported by Šimková (2021) proposed that L-moments are the most accurate estimators for higher quantiles of the interest rate compared to moments and maximum likelihood methods (MLE). Furthermore, it is most effective when the tail of the distribution is heavier, and the sample size is small. The minimal amount of data available is well recognized to raise the level of uncertainty in both parameter and quantile estimates (Blain et al., 2021).

As a result, properly using the L-moments approach with desired constraints can help solve this problem. One of the interesting issues made by Shahzad et al. (2021) is that the L-moment can be represented for any random variable with a mean. Since the mean considers all data values, it is often applied to generate a better approximation of population parameters. Even though L-moment is more reliable than other traditional procedures, the underlying equations necessary to determine the L-moment parameters are difficult to solve and require a deep understanding of mathematics (Ilaboya and Otuaro, 2019). Thus, it can be summed up that L-moments are very easy to perceive as interval estimation, hypothesis testing, and estimation parameters and are very straightforward to understand as indicators of distributional form since they assist in summarising theoretical distributions and empirical samples. These advantages are especially relevant when data has heavy tails, severe skewness, or large variations. The statistical and probabilistic methods were applied to past events to forecast the exceedance likelihood of future events to minimize risk and maximize efficiency in design (Smithers and Schulze, 2001). However, this may be a concern when single station data are to be used. Reliable estimations require long station records and histories (Malekinezhad & Zare-Garizi, 2014). Therefore, flood frequency analysis (FFA) is utilized to forecast and justify extreme flood events to the more soluble issue of fitting distributions to the bulk of the data with the aid of refinement of techniques for incorporating historical and palaeoflood data (Kidson & Richards, 2005). In Malaysia, FFA is widely used for the river basin distributions such as LG, GEV, GP, L3 and GL distribution (Yue & Wang, 2004; Badyalina et al., 2014; Badyalina et al., 2015; Badyalina et al., 2021). According to Maposa & Cochran (2017), the Generalized Pareto distribution (GPD) models produced in this study were found to be statistically worthwhile for fitting flood heights in the lower Limpopo River basin of Mozambique and proven to be a better match compared to time-homogeneous GPD models based on the GOF. Similarly, it also applied to rainfall extremes for nine locations in the Lake Victoria basin (LVB) in Eastern Africa. Based on this finding, one of the best parameter estimation methods is L-moments, and moreover, normal-tailed GPD was found suitable to assess the observed and large number of global climate model rainfall time series (Onyutha & Willems, 2015). Apart from that, generalized extreme value distribution (GEV) has been known to be extremely useful, especially in regional flood frequency. In this approach, the shape parameter k of the GEV distribution and the ratio of size and location parameters are consistent throughout all basins in the region (Morrison & Smith, 2002). In the study conducted by Nimac et al. (2022), GEV was employed to estimate the return value curves for the Zagreb-Grič station from 1908 until 2020. The analysis showed that short-duration wet events (rainfall levels greater than the appropriate 10-year return values) became increasingly common after the 1970s. In Pakistan, three GOF tests, namely Kolmogorov–Smirnov, Anderson–Darling, and Chi-squared, were used to the fitted distributions at the 5% significant level. The analysis is performed using annual maximum discharge data from 1980 to 2016, and the results show that the generalized extreme value distribution (GEV) and the lognormal distribution are the top two distributions for all locations (Badyalina et al., 2013; Badyalina et al., 2016; Badyalina et al., 2021; Farooq et al., 2018). Meanwhile, log-Pearson distribution (P3) is widely employed in hydrologic fields. P3 distribution provides a reasonable model of the distribution of annual United States flood data. L-moment ratio relationships for the P3 distribution are then improved to be used to compare a region's summary statistics (Griffis & Stedinger, 2007). In similar cases in Tunisia, L - moments are used in identifying regional flood frequency distributions, which fully employed GOF from L-skewness and L-kurtosis. The most frequently used distributions are GEV, GL, GP, L3 and LG. The GNO distribution was shown to be the best-suited flood frequency distribution, while the GNO and GEV distributions provide the best fit in central and southern Tunisia (Abida& Ellouze, 2008).

2. Methodology

Hosking (1990) proposed L-moments as a linear combination of probability-weighted moments (PWMs). Assume $x_{1:n} \le x_{2:n} \le \ldots \le x_{n:n}$ are the data in a specific order with a sample size of n. Based on Badyalina et al. (2021), the procedure of unbiased sample estimator of the L Moments is as follows:

$$b_r = \frac{1}{n}\binom{n-1}{r}^{-1}\sum_{i=r+1}^{n}\binom{i-1}{r}x_{i:n} \tag{1}$$

From Eq.1, we can obtain the first four components of L-Moments.

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

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

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

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

The first four sample estimates for L-moments are referred to as:

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

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

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

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

The samples of the L-moments ratio are addressed as follows:

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

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

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

Table 2 provides the potential probability distribution that has been employed in this study, namely GEV, GL, GP, L3 and LG. In Table 2, the estimation of the parameters for each potential distribution is described.

Table 2. Parameter estimation for potential distribution using L-Moment Method

Dist	**Cumulative Density function**	**Parameter Estimation**
GEV	$x(F) = \hat{\xi} + \frac{\hat{\alpha}}{\hat{k}}\left\{ 1 - (-\ln(F))^{\hat{k}} \right\}$	$\hat{k} = 7.85890c + 2.9554c^2$ where $c = \frac{2}{3+t_3} - \frac{\ln 2}{\ln 3}$ $\hat{\alpha} = \frac{l_2}{\Gamma(\hat{k})(1-2^{\hat{k}})}$; $\hat{\xi} = l_1 - \frac{\hat{\alpha}}{\hat{k}} + \hat{\alpha}\Gamma(\hat{k})$
GL	$x(F) = \hat{\xi} + \frac{\hat{\alpha}}{\hat{k}}\left[1 - \left\{ \frac{(1-F)}{F} \right\}^{\hat{k}} \right]$	$\hat{k} = -t_3$; $\hat{\alpha} = \frac{l_2}{\Gamma(\hat{k})[\Gamma(1-\hat{k}) - \Gamma(2-\hat{k})]}$

		$\hat{\varepsilon} = l_1 - \frac{\hat{\alpha}}{\hat{k}} + \hat{\alpha}\Gamma(\hat{k})\Gamma(1-\hat{k})$
GP	$x(F) = \hat{\xi} + \frac{\hat{\alpha}}{\hat{k}}\left\{1-[1-F]^{\hat{k}}\right\}$	$\hat{k} = \frac{1-3t_3}{1+t_3}$; $\hat{\alpha} = l_2(\hat{k}+1)(\hat{k}+2)$ $\hat{\xi} = l_1 - \frac{\hat{\alpha}}{\hat{k}} + \frac{\hat{\alpha}}{\hat{k}(\hat{k}+1)}$
LG	$x(F) = \alpha + e^{\xi+uk}; \quad u = \Phi^{-1}[1-F]$	$\hat{k} = -0.001005 + 0.997386z + 0.001027z^2 - 0.005853z^3 - 0.000154z^4 + 0.000141z^5$ where $z = \sqrt{\frac{8}{3}}\Phi^{-1}\left[\frac{1+t_3}{2}\right]$, Φ^{-1} is an inverse CDF of Normal Distribution. $\alpha = \ln(l_2) - \ln\left(2S_1(k) - e^{\frac{k^2}{2}}\right)$; $\xi = l_1 - e^{\alpha+\frac{k^2}{2}}$
L3	$x(F) = \hat{\xi}\hat{k} + K_T\sqrt{\hat{\xi}^2\hat{k}}$ where $K_T = \frac{2}{C_s}\left[\left\{\frac{C_s}{6}\left(\Phi^{-1}[1-F] - \frac{C_s}{6}\right)+1\right\}^3 - 1\right]$ $C_s = \frac{2}{\sqrt{\hat{k}}}$	$\hat{k} = 0.0127331632 + \frac{1.0246130369}{3\pi(t_3)^2} - \frac{0.0024863669}{(3\pi(t_3)^2)^2} + \frac{0.0001169073}{(3\pi(t_3)^2)^3} - \frac{0.0000027751}{(3\pi(t_3)^2)^4} + \frac{0.0000000323}{(3\pi(t_3)^2)^5} - \frac{0.0000000001}{(3\pi(t_3)^2)^6}$ $\hat{\alpha} = \frac{l_2}{2S_1(\hat{k})-\hat{k}}$; $\hat{\xi} = l_1 - \hat{k}\hat{\alpha}$ $S_r(k) = \int_0^\infty \left[\int_0^x \frac{1}{\Gamma(\hat{k})} t^{\hat{k}-1}e^{-t}dt\right]^r \frac{1}{\Gamma(\hat{k})} x^{\hat{k}} e^{-x} dx$

2.3 Evaluation Criteria

2.3.1 Accuracy Indicators

In accuracy indicators, three accuracy indicators are used in this study; namely, root mean square error (RMSE), mean absolute error (MAE) and mean absolute error (MAE). The MAE, MAPE and RMSE is define in Eq.13-Eq. 15, respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |F(y_i) - F(\hat{y}_i)| \tag{13}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{F(y_i) - F(\hat{y}_i)}{F(y_i)}\right| \tag{14}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(F(y_i) - F(\hat{y}_i))^2}{n}} \tag{15}$$

where $F(y_i)$ represent the actual data, n represent the total number of data, $\bar{F}(y_i)$ represent the average of the actual data and $F(\hat{y}_i)$ represent the estimated return period from the chosen distribution.

2.3.2 L-Moment Ratio Diagram

Hosking and Wallis (1993) proposed an L-Moment Ratio Diagram to identify the ideal distribution at the selected river basin. The L-Moment ratio diagram demonstrates the conceptual relation among both t_3 and t_4. The value of t_3 drawn from the peak flow data and plotted to L-Moment ratio diagram to identify which distribution lies closely.

2.3.3 GOF

Several applicable statistical procedures, such as the GOF tests, can be used to assess whether the probability distributions are appropriate for a particular study. The GOF tests can be used to justify choosing the best distribution in FFA (Badyalina et al.,2021). Two GOF tests, the Kolmogorov-Smirnov (KS) and Anderson Darling (AD) tests are employed in this study to determine how closely the observed data resembles the distributions.

3. Results and Discussion

Peak flow is generally related to implementing and developing flood management design. This information is essential for flood design at the targeted catchment. This study's targeted catchment is a Kelantan, Malaysia river. The annual peak flow is analyzed by fitting five normal distributions: GEV, GL, GP, L3 and LG. The estimated parameters for the potential distributions using L-Moments are shown in Table 3.

Table 3. Parameters for the candidate distributions

	Parameters		
Dist.	$\hat{\alpha}$	$\hat{\xi}$	$\hat{k}$
GEV	3379.46	2159.52	0.097
GL	4189.48	1352.17	-0.11
GP	841.06	5774.65	0.61
L3	4435.51	2478.35	0.67
LG	-6526.70	9.28	0.22

Table 3 shows the estimated parameters for the candidate distributions. The $\hat{\alpha}$, $\hat{\xi}$ and $\hat{k}$ are for GEV distributions are 3379.46, 2159.52 and 0.097, respectively. The $\hat{\alpha}$, $\hat{\xi}$ and $\hat{k}$ are for GL distributions are 4189.48, 1352.17 and -0.11, respectively. The $\hat{\alpha}$, $\hat{\xi}$ and $\hat{k}$ are for GP distributions are 841.06, 5774.65 and 0.61, respectively. The $\hat{\alpha}$, $\hat{\xi}$ and $\hat{k}$ are for L3 distributions are 4435.51, 2478.35 and 0.67, respectively. The $\hat{\alpha}$, $\hat{\xi}$ and $\hat{k}$ are for LG distributions are -6526.70, 9.28 and 0.22, respectively.

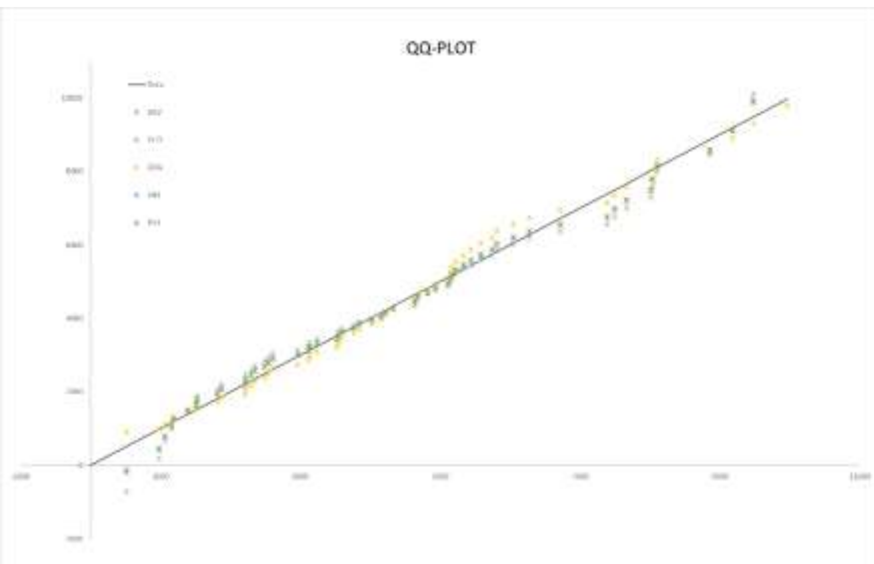

Figure 1. QQ-Plot for Sungai Kelantan river basin annual peak flow and potential distributions

Figure 1 illustrates QQ-plot for the annual peak flow of the Kelantan River basin and potential distribution. The QQ-plot is a visual tool for comparing potential distributions. Compared to other potential distributions, the GP distribution closely resembles the black line based on observational observations. Accuracy indicators, the GOF test, and the L-Moment Diagram are added to the study to complement our visual method-based observation. The GOF test, a numerical accuracy measure, and an L-moment ratio diagram are the 3 measuring methods employed in this study to pick the most suitable model. This study uses the rank score technique to analyze the best distribution that fits the target basin. This method called for grading each distribution according to how well it resembled the real observation. A score of 5 is awarded for the best distribution that fits the data. A score of 1 is given to the distribution with the poorest fit. P-Value is employed to evaluate the GOF test distribution test. The larger P-value implies that the distribution fits the data well. In the L-moment diagram, estimations of the dimensionless ratios t_3 and t_4 are compared using sample data values. The distribution with the least RMSE, MAE, and MAPE is awarded the highest possible score of 5. The distribution with the largest MAPE, RMSE, and MAE is awarded the lowest possible score of 1.

Table 4. Rank score for potential distribution

Potential Distribution	GEV	GL	**GP**	L3	LG
MAPE	3	2	**5**	4	1
KS	4	2	**5**	1	3
AD	3	2	**5**	1	4
GLRMSE	3	1	**5**	4	2
MAE	3	1	**5**	2	4
LMR	4	2	**5**	1	3
Total Score	20	10	**30**	13	17

Table 4 demonstrates that the GP distribution is optimal for describing yearly peak flow data for the Kelantan River. After evaluating each distribution individually, Table 4 indicates that the GL distribution is unsuitable, as its rank score is the lowest. The GP distribution is ranked higher than the other distributions used in this investigation. Due to the unique characteristics of each river's data series, it is difficult to establish a particular probability distribution for all streamflow basins in Kelantan. The annual peak flow data fluctuates dramatically from year to year due to the unpredictability of the weather brought on by climate change. Estimating extreme streamflow with varying return times is the purpose of selecting the "optimal" model for each location. Consequently, various return periods of streamflow are predicted using the best suitable frequency model. Table 5 shows the estimated return period.

Table 5. Estimated peak flow for the Kelantan River basin

	Estimated peak flow (m^3/s)				
Return Period (Years)	GEV	GL	**GP**	L3	LG
2	4157.05	4189.48	**4108.82**	4162.17	4164.14
10	7745.44	7546.83	**8005.92**	7735.56	7717.18
25	9318.14	9325.80	**9010.31**	9286.64	9294.75
50	10394.90	10745.44	**9474.11**	10360.86	10405.59
100	11393.47	12256.66	**9778.72**	11376.43	11471.25
200	12323.38	13876.08	**9978.78**	12347.38	12505.20

4. Conclusion

FFA is suitable for predicting the long-term flow characteristics of a river. This study sought to determine the ideal potential distribution for FFA to represent the annual peak flow in the Kelantan River basin. GEV, GL, GP, L3 and LG are the distributions employed, representing the five most often used distributions in the analysis of extreme hydrologic variables. Regional flood frequency study has utilized L-moment because of the robustness of its GOF, which is superior to traditional single-basin GOF. The annual peak flow series data collected from the historical daily stream flow record of the Kelantan River basin in Malaysia is applied to the five potential distributions. The model's evaluation uses the L-Moment Ratio Diagram and numerical performance criteria. Based on the performance evaluation, GP distribution is found to be optimal for describing yearly peak flow data for the Kelantan River. In future research, it would be interesting to implement the distribution to several rivers located near Kelantan River for regional FFA or in-situ FFA to provide guidance about the expected behaviour of future flooding.

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