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Use of Goodness-of-Fit Test in Flood Frequency Estimation: A Case Study for Sri Lankan Catchments

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Abstract - *The selection of a probability distribution for annual maximum discharges was carried through exploratory and confirmatory stages. The L-moment diagram was applied first in order to screen out inappropriate candidate distributions. The goodness-of-fit test was then applied in order to examine the descriptive performance of screened distributions. The effectiveness of this two-stage procedure was studied on an ensemble of diverse annual maximum discharge series recorded in Sri Lanka. The generalized logistic distribution was the only one of a number of candidate distributions whose theoretical relationship between L-moments followed closely enough the actual relationships in the case study. This distribution was well fitted to 27 of the discharge series, and satisfactorily fitted to the entire ensemble. It was concluded that such a two-stage procedure, which applies quantitative measures in both stages, would reduce the subjectivity involved with the selection of a probability distribution, thus improving the credibility of predicted high discharges.*

Keywords: Flood frequency, L-moment, goodness-of fit, regional flood

1 Introduction

The association of the magnitude of high discharges with their exceedance frequency is often requested from hydrologists. This is traditionally fulfilled by the use of a probability distribution which is selected with respect to its coherence with data for a region in which the site of interest is located and adapted to the properties of that site. The selection of the distribution is a process involving a number of decisions. A rational practice for reducing the effect of subjectivity in these decisions involves the use of common procedures and objective techniques. These include, amongst the others, widening of the region's boundaries (e.g. selection of the same probability distribution for as wide a region as deemed permissible), and the quantitative examination of the coherency of candidate distributions with the data [1]. The selection of such examinations is another decision requiring resolution. This article contributes to the resolution process by proposing a combination of measures and applying them for a region of diverse hydrologic behaviour.

This procedure makes assumptions such as observations at any given site being identically distributed, observations at any given site being serially independent, and observations at different sites being independent. The first two of the 3 mentioned assumptions are plausible for many kinds of data, particularly for annual totals or extremes, which are free from seasonal variations. It is a basic assumption of most methods of frequency analysis that the events observed in the past are likely to be typical of what may be expected in the future. This assumption may be undermined when obvious sources of time trends are present. Frequency distributions for streamflow data, for example, are affected by changes in land use and by artificial regulation of the flow. When sites affected by such obvious sources of nonstationarity are removed from the data set, the assumption of

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identical distributions for a site's observations is often reasonable. The effect of serial dependence on at-site frequency analysis has been investigated [2, 3]. Considering frequency distributions of extreme-value type I and log-Pearson type III, respectively, and it has been found that serial dependence caused a small amount of bias and a small increase in the standard error of quantile estimates.

The results of the goodness-of-fit test are sensitive to the fit of the distribution to the tails of the data [4], a property valuable for cases where discharges of rare exceedance probabilities are considered [5]. In this context, it is worth mentioning the work of Shen [6] regarding the effect of tail behaviour assumptions upon flood prediction. They conclude that distributions such as the Pareto and the Log-Pearson type-three functions (Ref. Table 1) are more conservative than the Normal, Gamma, Log-Normal and other distributions.

Table 1: *Flood quantile distributions (Source: Hosking. 1986)*

Distribution	Code	Number of parameters	Parameters	$F(x)$, $x(F)$
Exponential	EXP	2	$\xi\ \alpha$	$F=1-\exp\{-(x-\xi)/\alpha\}$ $x=\xi-\alpha\log(1-F)$
Gamma	GAM	2	$\alpha\ \beta$	$F=G(x/\beta,\alpha)$ $x(F)$ not explicitly defined
Generalized extreme-value	GEV	3	$\xi\ \alpha\ k$	$F=\exp[-\{1-k(x-\xi)/\alpha\}^{1/k}$ $x=\xi+\alpha\{1-(-\log F)^k\}/k$
Generalised logistic	GLO	3	$\xi\ \alpha\ k$	$F=1/[1+\{1-k(x-\xi)/\alpha\}^{1/k}]$ $x=\xi+\alpha[1-\{(1-F)/F\}^k]/k$
Generalized Normal	GNO	3	$\xi\ \alpha\ k$	$F=\Phi[-k^{-1}\log\{1-k(x-\xi)/\alpha\}]$ $x(F)$ not explicitly defined
Generalised Pareto	GPA	3	$\xi\ \alpha\ k$	$F=1-\{1-k(x-\xi)/\alpha\}^{1/k}$ $x=\xi+\alpha\{1-(1-F)^k\}/k$
Gumbel	GUM	2	$\xi\ \alpha$	$F=\exp[-\exp\{-(x-\xi)/\alpha\}]$ $x=\xi+\alpha\log(-\log F)$
Kappa	KAP	4	$\xi\ \alpha\ k\ h$	$F=[1-h\{1-k(x-\xi)/\alpha\}^{1/k}]^{1/h}$ $x=\xi+\alpha[1-\{(1-F)^h/h\}^k]/k$
Normal	NOR	2	$\mu\ \sigma$	$F=\Phi\{(x-\mu)/\sigma\}$ $x(F)$ not explicitly defined
Pearson type III	PE3	3	$\mu\ \sigma\ \gamma$	$F=G\left((x-\mu+2\sigma/\gamma)/\lvert\frac{1}{2}\sigma\gamma\rvert, 4/\gamma^2\right),\quad \gamma>0$ $F=1-G\left(-(x-\mu+2\sigma/\gamma)/\lvert\frac{1}{2}\sigma\gamma\rvert, 4/\gamma^2\right),\ \gamma<0$ $x(F)$ not explicitly defined
Wakeby	WAK	5	$\xi\ \alpha\ \beta\ \gamma\ \delta$	$F(x)$ not explicitly defined $x=\xi+\frac{\alpha}{\beta}\{1-(1-F)^\beta\}-\frac{\gamma}{\delta}\{1-(1-F)^{-\delta}\}$

$G(x,\alpha)=\{\Gamma(\alpha)\}^{-1}\int_0^x t^{\alpha-1}e^{-t}\,dt$ is the incomplete gamma integral

$\Phi(x)=(2\pi)^{-1/2}\int_{-\infty}^x \exp(-t^2/2)\,dt$ is the standard Normal cumulative distribution function.

A new procedure of analysis, which views L-moment diagrams for the data series, has recently been proposed [7-9], and examples for its application have been demonstrated [10-12]. L-moments are statistical parameters of a series which are computed through linear combinations of the data values when they are ranked according to their magnitudes. A description of the L-moment method is given by Gamage [12]. The application of L-moments for distribution selection culminates in a diagram presenting the L-skewness (τ_3) versus the L-kurtosis (τ_4) values for discharge series in the considered region. The theoretical values of these moments for a number of candidate distributions are also plotted on the diagram. The distribution, around whose values the data points for the different series are best concentrated, is selected for application.

Published diagrams for a number of case studies exhibit a weak concentration of L-moment values for considered regions around the candidate distributions [11]. This might lead to the conclusion that such diagrams do not help in discriminating between distributions [13]. In order to overcome such difficulties, Hosking and Wallis [8] proposed to limit the application of these diagrams to homogeneous regions. They formulated a suitable homogeneity test, and recommended deciding upon the suitability of candidate distributions with respect to their distance from the weighted average of the L-moments for the series [15]. The effectiveness of the goodness-of-fit procedure is examined by means of this case study.

2 Description of Data Used

Locations of the 65 sites selected after screening are shown given in [12]. It was found that certain sites were regulated after some years. Those data were removed from this analysis. The selected data set contains a total of 1494 stream flow observations of the period 1940 to 2000. The range of record lengths at the gauging stations is from 10 to 54 years of annual maximum daily flow values with a mean record length of 23 years and a median length of 22 years. The catchment drainage areas range from 45 km^2 to 3071 km^2 with an average value of 646 km^2 and a median value of 345 km^2. Other information such as discordancy statistics for site i (D_i) of the selected sites [12] is given in Table 2.

3 Goodness-of-fit Test

The aim of the goodness-of-fit is to test whether a given distribution fits the data acceptably closely. A related aim is to choose, from a number of candidate distributions, the one that gives the best fit to the data. To this end, a set of candidate three-parameter distributions as given in Table 1 was assembled. Reasonable possibilities include the Generalized Pareto, Generalized Extreme Value, Generalized Logistic, Generalized Normal, and Pearson Type III distributions. The goodness-of-fit criterion for each of various distributions is defined in terms of L-moments and is termed the Z-statistic [8]:

$$Z^{DIST} = \frac{\left(\tau_4^{DIST} - \bar{\tau}_4 + \beta_4\right)}{\sigma_4} \qquad (1)$$

where DIST refers to a candidate distribution, τ_4^{DIST} is the population L-kurtosis of selected distribution, $\bar{\tau}_4$ is the sample L-kurtosis, β_4 is the bias of sample L-kurtosis defined as:

$$\beta_4 = \frac{1}{N_{sim}} \sum_{m=1}^{N_{sim}} \left(\bar{\tau}_{4_m} - \bar{\tau}_4\right) \qquad (2)$$

where N_{sim} is the number of simulations and σ_4 is the standard deviation of sample L-kurtosis defined as:

$$\sigma_4 = \sqrt{\frac{1}{N_{sim}-1} \sum_{m=1}^{N_{sim}} \left(\bar{\tau}_{4_m} - \bar{\tau}_4\right)^2 - N_{sim}\beta_4^2} \qquad (3)$$

A four parameter kappa distribution is fitted to the sample L-moment ratios. The kappa distribution is used to simulate 500 regions similar to the observed region, and from these simulations β_4 and σ_4 are estimated. Hosking and Wallis [14]

Table 2: *Information of the selected sites*

Site No	Name	Area (km^2)	Elevation (m)	Num. of Records	Lat. (N) (Deg.)	Lon. (E) (Deg.)	Q_{mean} (m^3/s)	D_i	Best distribution
1	Glencourse	1463	18	12	6.9750	80.1808	1239.25	0.51	EGV,PE3
2	Matiyadola	606	20	12	7.0261	80.2739	767.83	7.50 **	GLO
3	Algoda Bridge	345	26	15	6.9486	80.2611	645.93	1.50	GNO
4	Daraniyagala	152	82	28	6.9250	80.3375	332.46	0.88	GLO
5	Kitulgala	388	56	13	6.9917	80.4125	836.62	0.32	PE3
6	Maussakele	122	1158	11	6.8375	80.5500	336.45	0.69	PE3

** - *discordant;* ++ - *not accepted by the goodness-of-fit test*

recommend that only distributions for which $|Z^{DIST}| \leq 1.64$ should be considered as suitable distributions for the particular site.

4 Results and Discussion

A convenient way of representing the L-moments of different distributions is the L-moment ratio diagram, exemplified by Figure 1. This shows the L-moments on a graph whose axes are L-skewness and L-kurtosis. A two-parameter distribution with a location and a scale parameter plots as a single point on the diagram. A three-parameter distribution with location, scale, and shape parameters plots as a line, with different points on the line corresponding to different values of the shape parameter.

The L-moment ratios as well as their regional averages are calculated for the selected sites. The τ_3 versus τ_4 moment ratio diagram for different stations is shown in Fig. 1. Following Vogel [11], five curves and five points, representing theoretical relationships for popular distributions, are plotted in Fig. 1. These are the Exponential, Gumbel, Logistic, Normal, Uniform, Generalized Pareto, Generalized Extreme Value, Generalized Logistic, Generalized Normal, Pearson Type III distributions. As one might expect for such a large region, the results in Fig. 1 suggest that the region as a whole is heterogeneous. Data points are widely scattered in Fig. 1. This conclusion is also supported by the results obtained from the regional homogeneity test [8, 12]. Values of the site discordancy measure D_i, the heterogeneity measure H, and the goodness-of-fit measure (Z^{DIST}) were computed for the whole region. Three sites, site numbers 2, 55, and 58, were found to be discordant with the region of 65 sites as a whole (Table 2). The heterogeneity measures H = 11.56 indicates a very high degree of heterogeneity in the selected sites as a region.

The main conclusion from the prior analysis is that the selected sites are statistically heterogeneous. For the region as a whole the goodness-of-fit measure for different distributions are Generalized Logistic = -0.47, Generalized Extreme Value = -2.99, Generalized Normal = -4.52, Pearson Type III = -7.19, and Generalized Pareto = -9.48. The Generalized Logistic distribution seems to be the best choice if the region is to be considered as a single unit.

One of the strengths of regional frequency analysis using the regional L-moment algorithm is that it is useful even when not all of its assumptions are satisfied. A realistic assessment of the accuracy of estimates should therefore take into account the possibility of heterogeneity in the region, misspecification of the frequency distribution, and statistical dependence between observations at different sites, to an extent that is consistent with the data. A reasonable approach is to estimate the accuracy of estimated quantiles by Monte Carlo simulation. The simulations should be matched to the particular characteristics of the data from which the estimates are calculated. The region used as the basis for simulation should be chosen to have the same number of sites, record length at each site, and regional average L-moment ratios as the actual data.

As noted above, it will often be appropriate for the simulated region to include heterogeneity, misspecification, and intersite dependence or some combination thereof.

In the simulation procedure, quantile estimates are calculated for various nonexceedance probabilities. At the m^{th} repetition, let the site-i quantile estimate for nonexceedance probability F be $\hat{Q}_i^{[m]}(F)$. The relative error of this estimate is $\{\hat{Q}_i^{[m]}(F)-Q_i(F)\}/Q_i(F)$. This quantity can be squared and averaged over all M repetitions to approximate the relative RMSE of the estimators. The relative RMSE is approximated, for large M, by

$$R_i(F)=\left[M^{-1}\sum_{m=1}^{M}\left\{\frac{\hat{Q}_i^{[m]}(F)-Q_i(F)}{Q_i(F)}\right\}^2\right]^{1/2} \quad (4)$$

A summary of the accuracy of estimated quantiles over all of the sites in the region is given by the regional average relative root mean square error (RMSE) of the estimated quantile,

$$R^R(F)=N^{-1}\sum_{i=1}^{N}R_i(F) \quad (5)$$

In addition to the overall accuracy measures for quantile estimates, Eqs. (4) and (5), analogous quantities can be calculated for the growth curve estimate. Let the growth curve for site i be $q_i(F)$, defined by

$$Q_i(F)=\mu_i q_i(F) \quad (6)$$

Other useful quantities, particularly when the distribution of estimates is skew, are the empirical quantiles of the distribution of estimates. These can be obtained by calculating the ratio of estimated to true values, $\hat{Q}_i(F)/Q_i(F)$ for quantiles and $\hat{q}_i(F)/q_i(F)$ for the growth curve, averaging these values over the sites in the region, and accumulating over the different realizations a histogram of the values taken by the ratio. For example, for a particular nonexceedance probability F it may be found that 5% of the simulated values of $\hat{Q}_i(F)/Q_i(F)$ lie below some value $L_{.05}(F)$ whereas 5% lie above some value $U_{.05}(F)$. Then 90% of the distribution of $\hat{Q}_i(F)/Q_i(F)$ lies within the interval

$$L_{.05}(F)\le\frac{\hat{Q}(F)}{Q(F)}\le U_{.05}(F) \quad (7)$$

and inverting this to express Q in terms of $\hat{Q}$ gives

$$\frac{\hat{Q}(F)}{U_{.05}(F)}\le Q(F)\le\frac{\hat{Q}(F)}{L_{.05}(F)} \quad (8)$$

The regional average relative RMSE of the estimated growth curve was calculated from the simulations. Quantiles of the distribution of the regional average of the ratio of the estimated to the true at-site growth curve, were computed from a histogram accumulated during the simulations. From these quantiles the 90% error bounds for the growth curve were computed analogously to Eq. (8). The results are given, for selected values of the return period T, in Table 3.

Table 3: *Accuracy measures for estimated growth curve of the 65 catchments selected*

T	$\hat{q}_i(F)$	RMSE	90% Error bounds	
2	0.995	0.141	0.887	1.019
10	1.245	0.109	1.135	1.274
20	1.333	0.18	1.159	1.415
50	1.448	0.28	1.162	1.606
100	1.535	0.359	1.149	1.754
1000	1.834	0.673	1.029	2.251

The quantile estimates of the at-site distributions for the 6 catchments are given in Tables 4-8. Although these tables, Table 2 and 4-8, were completed for all 65 catchments, due to page limitation we present only the data for 6 of the catchments. The full table may be obtained by the interested reader from the author. For these catchments, the Generalized Logistic distributions seem to give the best at-site estimates with 27 catchments having lowest Z^{DIST} while the Generalized Pareto distribution gives best estimates for 15 sites. the Generalized Extreme Value distribution gives best estimates for 10 sites. the Generalized Normal distribution gives best estimates for 8 sites, and the Pearson Type III distribution gives best estimates for 7 sites as shown in Table 2.

Table 4: *Goodness of fit, parameter estimates, and quantile estimates for GLO distribution*

Site Number	Name	Goodness-of-fit (Z)	Parameters			Normalized Flow Quantiles (Q/Qmean)				
			ξ	α	k	T=2	T=10	T=20	T=50	T=100
1	Glencourse	0.82	0.974	0.170	-0.092	0.974	1.388	1.549	1.770	1.947
2	Matiyadola	-0.65	1.038	0.137	0.163	1.038	1.291	1.358	1.432	1.481
3	Algoda Brodge	0.68	0.922	0.152	-0.285	0.922	1.385	1.621	2.003	2.362
4	Daraniyagala	-1.40	0.886	0.189	-0.324	0.886	1.490	1.815	2.359	2.884
5	Kitulgala	1.02	0.904	0.237	-0.232	0.904	1.583	1.905	2.402	2.848
6	Maussakele	0.96	0.954	0.153	-0.176	0.954	1.365	1.546	1.811	2.038

Table 5: *Goodness of fit, parameter estimates, and quantile estimates for GEV distribution*

Site Number	Name	Goodness-of-fit (Z)	Parameters			Normalized Flow Quantiles (Q/Qmean)				
			ξ	α	k	T=2	T=10	T=20	T=50	T=100
1	Glencourse	0.21	0.871	0.276	0.124	0.970	1.412	1.556	1.723	1.837
2	Matiyadola	-1.67	0.950	0.282	0.601	1.043	1.298	1.341	1.375	1.390
3	Algoda Bridge	0.37	0.837	0.208	-0.172	0.916	1.410	1.645	1.996	2.298
4	Daraniyagala	-1.66	0.783	0.252	-0.226	0.879	1.521	1.849	2.360	2.821
5	Kitulgala	0.63	0.769	0.340	-0.094	0.896	1.622	1.935	2.373	2.728
6	Maussakele	0.47	0.865	0.231	-0.009	0.949	1.390	1.560	1.782	1.949

Table 6: *Goodness of fit, parameter estimates, and quantile estimates for GNO distribution*

Site Number	Name	Goodness-of-fit (Z)	Parameters			Normalized Flow Quantiles (Q/Qmean)				
			ξ	α	k	T=2	T=10	T=20	T=50	T=100
1	Glencourse	0.27	0.971	0.301	-0.189	0.971	1.408	1.552	1.727	1.851
2	Matiyadola	-1.25	1.042	0.242	0.336	1.042	1.294	1.348	1.401	1.433
3	Algoda Bridge	0.15	0.913	0.266	-0.595	0.913	1.425	1.656	1.984	2.251
4	Daraniyagala	-1.92	0.874	0.330	-0.680	0.874	1.548	1.873	2.349	2.748
5	Kitulgala	0.48	0.894	0.417	-0.481	0.894	1.633	1.940	2.356	2.682
6	Maussakele	0.41	0.949	0.271	-0.362	0.949	1.391	1.559	1.775	1.939

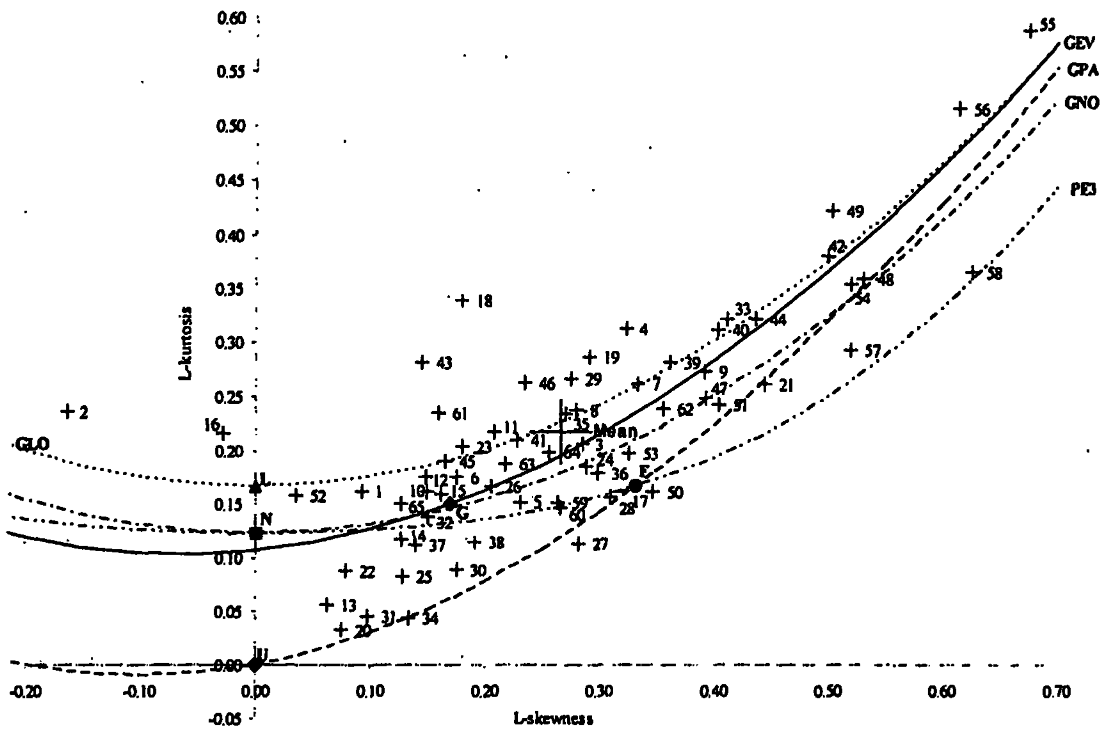
Table 7: *Goodness of fit parameter estimates, and quantile estimates for PE3 distribution*

Site Number	Name	Goodness-of-fit (Z)	Parameters			Normalized Flow Quantiles (Q/Qmean)				
			μ	σ	γ	T=2	T=10	T=20	T=50	T=100
1	Glencourse	0.21	1.000	0.309	0.565	0.971	1.409	1.552	1.723	1.843
2	Matiyadola	-1.41	1.000	0.261	-0.990	1.042	1.295	1.345	1.392	1.417
3	Algoda Bridge	-0.23	1.000	0.337	1.713	0.909	1.446	1.666	1.951	2.165
4	Daraniyagala	-2.36	1.000	0.449	1.944	0.865	1.586	1.894	2.299	2.604
5	Kitulgala	0.21	1.000	0.488	1.398	0.890	1.653	1.946	2.321	2.597
6	Maussakele	0.24	1.000	0.297	1.065	0.948	1.398	1.560	1.762	1.909

Table 8: *Goodness of fit, parameter estimates, and quantile estimates for GPA distribution*

Site Number	Name	Goodness-of-fit (Z)	Parameters			Normalized Flow Quantiles (Q/Qmean)				
			ξ	α	k	T=2	T=10	T=20	T=50	T=100
1	Glencourse	-1.02	0.541	0.763	0.662	0.965	1.442	1.535	1.607	1.639
2	Matiyadola	-3.22	0.459	1.502	1.779	1.058	1.290	1.300	1.303	1.304
3	Algoda Bridge	-0.47	0.632	0.409	0.112	0.905	1.462	1.672	1.927	2.102
4	Daraniyagala	-2.40	0.544	0.466	0.021	0.864	1.591	1.896	2.293	2.588
5	Kitulgala	-0.31	0.417	0.727	0.247	0.880	1.693	1.955	2.240	2.416
6	Maussakele	-0.59	0.612	0.544	0.403	0.941	1.429	1.559	1.684	1.752

Figure 1: L-moment ratio diagram for the 65 stations listed in Table 2. Distributions: E – Exponential, G – Gumbel, L – Logistic, N – Normal, U – Uniform, GPA – Generalized Pareto, GEV – Generalized Extreme Value, GLO – Generalized Logistic, GNO – Generalized Normal, PE3 – Pearson Type III.



5 Conclusion

Annual maximum flow data from 65 sites in Sri Lanka were analysed using L-moments to study regional homogeneity and assess goodness-of-fit in frequency analysis. The region as a whole is heterogeneous. A comparative study of the data with respect to the goodness of fit of at-site and regional quantile estimates revealed the following:

(a) Application of more than one quantitative procedure for the selection of a probability distribution contributes to the credibility of the selection.
(b) The L-moment diagram appears to be suitable for an exploratory stage where inappropriate distributions could be screened out.
(c) A goodness-of-fit test appears to be suitable for a confirmatory stage where descriptive performance of screened distributions is examined.
(d) For the present case study, the Generalized Logistic distribution is the only one of a number of candidate distributions to be favourably screened by the L-moment diagram and goodness-of-fit test.

References

1. N.P.D. Gamage. "Seasonality measures to find catchment similarity for regional flood frequency analysis of catchments in Sri Lanka". *Engineer*
2. *Journal of the Institution of Engineers, Sri Lanka.* Vol. xxxv, No: 3, pp. 7-16, 2002.
3. I.M. Landwehr, N.C. Matalas, and J.R. Wallis. "Probability weighted moments compared with some traditional techniques in estimating Gumble parameters and quantiles." *Water Resour: Res.*, Vol. 15, pp. 1055-1064, 1979.
4. T.A. McMahon, and R. Srikanthan. "Log Pearson type 3 distribution effect of dependence, distribution parameters and sample size on peak annual flood estimates". *Journal of Hydrology,* 52, 149-159, 1982.
5. M.A. Stephens, "Tests based on EDF statistics". In: R.B. D'Agostino and MA. Stephens (Editors), *Goodness-of-Fit Techniques.* Dekker, New York, pp. 97-193, 1986.
6. V. Klemes. "Hydrologic and engineering relevance of flood frequency analysis". In: V.P. Singh (Editor), *Hydrologic Frequency Modelling.* Reidel, Dordrecht, Netherlands, pp. 1-18, 1987.
7. H.W. Shen, M.C. Bryson, and I.D. Ochoa. "Effect of tail behavior assumptions on flood predictions". *Water Resour. Res.*, Vol. 16: pp. 361-364, 1980.
8. J.R.M. Hosking. "L-moments: analysis and estimation of distributions using linear combination of order statistics." *I. Royal Statist. Soc. B*, Vol. 52(1), pp. 105-124, 1990.
9. J.R.M. Hosking, J.R. Wallis. "Some statistics useful in regional frequency analysis", *Water Resour. Res.*, 29, 271—281, 1993.
10. J.R. Stedinger, R.M. Vogel, and E. Foufoula-Georgiou. "Frequency analysis of extreme events". In: DR. Maidment (Editor), *Handbook of Hydrology*, McGraw-Hill, New York, pp. 18.1-18.66, 1993.
11. R.M. Vogel, and N.M. Fennessey. "L-moment diagrams should replace product moment diagrams", *Water Resour. Res.*, Vol. 29: pp. 1745-1752, 1993.
12. R.M. Vogel, T.A. McMahon, and F.H.S. Chiew. "Floodflow frequency model selection in Australia", *J. Hydrol.*, pp. 146: 421-449, 1993.
13. N.P.D. Gamage. "Analysis of regional homogeneity of catchments in SriLanka by L-Moments", *Engineer Journal of the Institution of Engineers, Sri Lanka.* Vol. xxxiv, No. 2, pp. 78 – 87, 2001.
14. B. Onbz, and M. Bayazit. "Best-fit distributions for largest available flood samples." *J. Hydro.*, Vol. 167, pp. 195-208, 1995.
15. J.R.M. Hosking, J.R. Wallis. *Regional Frequency Analysis: An Approach Based on L-moments.* Cambridge University Press, UK, 1997.
16. Z. Zrinji, and D.H. Burn. "Regional flood frequency with hierarchical region of influence". *J. Water Resour. Plann. Manage.*, ASCE, Vol. 122: pp. 245-252, 1996.

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