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# Modelling the extreme floods of South Australian catchments

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**Abstract:** It has been nearly 15 years since the last South Australian (SA) regional flood studies were carried out. In addition to this in the last two decades a number of techniques have evolved for improving regional flood estimations. Because of these reasons and as part of the Australian Rainfall Runoff (AR&R) updates, this study was carried out to identify the best approach for regional flood frequency analyses in South Australia while incorporating 15 years of new flow data.

Australian Rainfall and Runoff (1987) recommends to use Log Pearson type 3 (LP3) fitted by Method of Moments (MOM) for Flood Frequency Analysis (FFA) in Australia. However, several studies (e.g. Vogel et al. 1993; Rahman, Weinmann & Mein 1999) have shown that the Generalized Extreme Value (GEV) distribution outperforms the LP3 distribution in estimation of more reliable flood quantiles. L moments introduced by Hosking (1990) are considered to be unbiased and perform better than the MOM in parameter estimation (Vogel and Fennessey 1993). Later, Wang (1997) illustrated that higher order LH moments are more efficient than L moments in fitting the GEV distribution function to more extreme floods.

This paper presents the work undertaken for initial catchment selection and data preparation followed by identification of the best order of LH moments for modelling floods in South Australia. A total of 30 gauged stations have been selected for at-site FFA, after the initial data screening process. Flood quantiles at Average Recurrence Intervals (ARIs) of 2, 5, 10, 20, 50 and 100 year have been estimated using L, L2 and L4 moments. Performance of each method in fitting GEV to the annual maximum series of the selected catchments was assessed visually by using probability plots. Although it was generally observed that GEV/L4 fits the upper tail of the observed data better than the other two moments, the plots did not demarcate clearly the best order of LH moments. Therefore, Monte Carlo simulations were conducted and best method was selected considering the Bias and Mean Square Errors (MSE) of the quantile estimates.

It was found that bias of L4 moment estimates have the least median Bias and dispersion relative to those of L2 and L moments. Box-plots of efficiency indicated that at larger recurrence intervals, L4 moments perform better than both L moments and L2 moments. Therefore, considering probability plots, bias and efficiency estimates, it was concluded that the GEV distribution fitted by L4 moments as the best model for flood frequency analysis in South Australia and was therefore selected to be used for regional flood frequency analysis.

***Keywords:*** *Flood frequency analysis, Data preparation, GEV, LH moments, Bias, Mean square error*

## 1. INTRODUCTION

Regional Flood Frequency Analysis (RFFA) is one method that allows the estimation of the flood magnitude at any stream location within a region. It attempts to respond to the need for flood estimation in ungauged basins and for improving the at-site estimate by using the available flood data from within a region assessed to have similar hydrology. It enables flood quantile estimates for any site in a region to be expressed in terms of flood data recorded at all gauging sites in that region, including those at the specific site. Providing reliable estimates of flood quantiles is essential and is applied in many engineering projects. As many of the streams in South Australia (SA) are ungauged or have little streamflow data, RFFA plays an important role in computing reliable flood quantile for such situations.

For predictions through RFFA to be reliable, the collected data at all sites must be of high quality. An initial screening of data should aim to verify that this requirement is satisfied. The method of data collection, measurement and the changes in the instrumentation may produce erroneous data. In addition to the above errors, poor quality flow information may be due to missing records, rating curve errors and rating curve extrapolation. As the erroneous and poor quality data reduce the reliability of the at-site flood frequency estimates, it is always important to assess the quality of the data being used prior to the flood frequency analysis.

Estimation of flood quantiles requires the frequency distribution of past flood magnitudes and the probability of occurrences of such floods. The most commonly used frequency distributions in hydrology can be divided into four groups; the normal family (Normal (N), Log-Normal (LN)), the General Extreme Value (GEV) family (GEV, Gumbel, log-Gumbel, Weibull), the Pearson type 3 family (Pearson type 3 (P3), Log-Pearson type 3 (LP3)) and the generalized Pareto distribution. Hosking and Wallis (1997) state that no one distribution can be the true distribution for all these stations; hence the aim is to identify the most appropriate flood frequency distribution for a site of the interest that makes more accurate flood quantiles.

There has been a significant advancement in parameter estimation methods during the last three decades. The L moments introduced by Hosking (1990) are considered to be unbiased and perform better than the product moments in parameter estimation (Vogel and Fennessey 1993). Later, Wang (1997) illustrated that higher order LH moments are more efficient than L moments in fitting the GEV distribution function to the more extreme floods. Although Wang (1997) recommends against using higher order moments above the L2 moments, recently it has been found by Meshgi & Khalili (2007) that performance of the different orders of LH moments is site specific. Thus, it is important to investigate different orders of LH moments, not restricting the investigation to L2 moments.

The specific objective of the work detailed in this paper was to screen the data and identify the best order of the LH moments for fitting GEV distribution to floods in South Australia. The GEV distribution was fitted to Annual Maximum Series (AMS) of the selected study catchments by using L, L2 and L4 moments and the performance of each method was assessed against a number of indicators including Bias and Mean Square Error (MSE). Details of the catchment selection and data preparation, methodology, results with discussion and concluding remarks are presented in this paper.

## 2. CATCHMENT SELECTION AND DATA PREPARATION

The reliability of regional flood estimations made for catchments with limited or no flow information is largely depend on the quality and representativeness of flood observations at the gauged stations used for RFFA. Poor quality of the gauge information could be due to one or more reasons such as missing records, rating curve extrapolation and rating curve errors. Therefore, it is important to assess the issues of the available gauge records and identify suitable remedial actions for improving the quality of the data. In this study this was achieved by (1) identifying the suitable gauge stations for FFA (2) minimising the errors associated with rating curve extrapolations; (3) treating the missing records and; (4) identifying and censoring outliers. The data used in SA flood study were sourced from the Department of Water, Land and Biodiversity Conservation (DWLBC) in South Australia.

In this study, the candidate catchments were selected to not have significant impoundment or abstraction. The suitability of a candidate catchment to be included in RFFA was investigated by considering the size of the catchments, lengths and quality of streamflow records, degree of regulation, urbanization and land use changes. The catchments having areas larger than $1000 km^2$ and having streamflow records less than 15 years were excluded at the start of the study.

There is always a trade-off between the exclusion of the catchments with poor quality data for improving the reliability of flood estimates and having the maximum possible information for the regional study. Hence, it is essential to treat and include poor quality data if possible as this will maximize the information available while minimising the errors associated with it. Two major issues in the streamflow data that will adversely affect the outcomes of RFFA were identified. They are; (1) Catchments with varying lengths of missing records ranging from few days to a number of years; and (2) Records with unrealistically high values of extrapolated data.

Missing records are treated in two ways. In the first approach, missing records are disregarded and annual peaks extracted from the available data. In the second approach missing records are infilled if there is a possibility of a significant peak flow within the missing record period. The main criterion that was used to examine whether or not the peak flow existed within the available data range was comparing flow records against the rainfall data. If rainfall information was not available at the particular time of interest or it didn't give enough evidence to prove that peak flow did not occur during the missing record period, streamflow records of a highly correlated catchment was used. Then the subjective judgements were taken to determine whether or not the annual peak exist within the available data range. Every catchment was checked against each other to identify the most correlated catchments using a function which is based on double mass plot technique in HYDSTRA. It was not possible to find the correlation between daily instantaneous streamflow data of two catchments. Hence, using daily mean streamflow data highly correlated catchments were identified for each of the catchments. The data infilling was then carried out using the correlation catchment to determine mean daily flow, and by the regression relationship between mean daily flows and instantaneous peak flows.

Rating curve extrapolation errors can be directly transferred into the largest observations in the annual maximum flood series, and it can result in inaccurate flood estimates. The degree of error of rating curve extrapolation was determined by Rating Ratio (RR) method (Haddad, Rahman, & Weinmann 2008). In this method, when RR increases the rating curve extrapolation error also increases results in considerable errors in flood frequency analysis. Therefore, the stations which had significantly higher RRs than normal were excluded from the study.

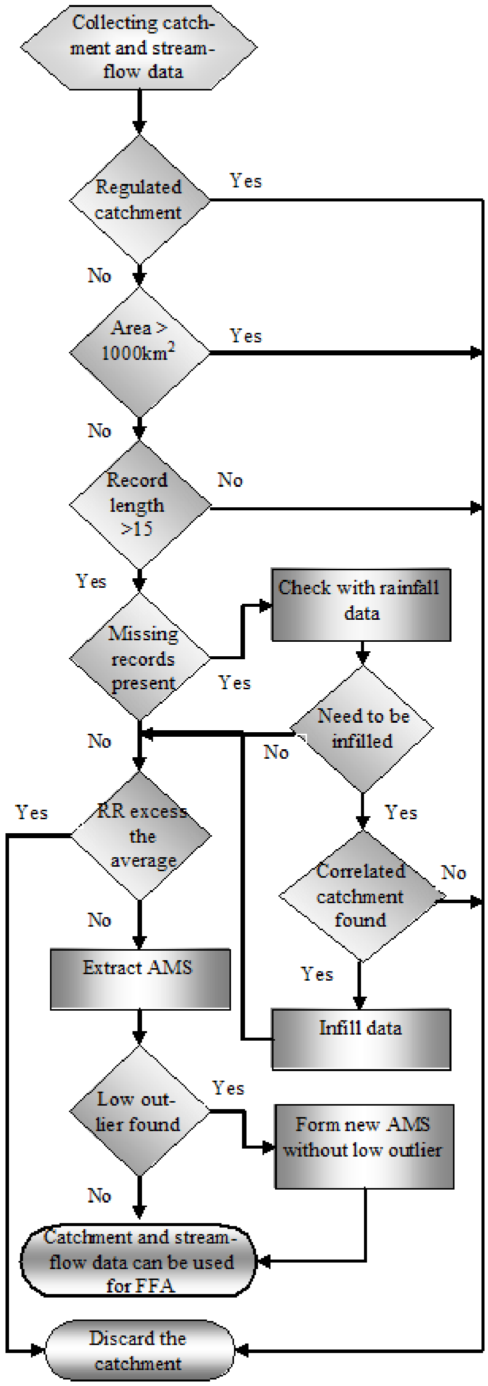


**Figure 1:** Conceptual framework for catchment selection and data preparation

Outliers can occur due to errors in data collection, or due to natural causes (drought or large flood). The presence of outliers causes difficulties when fitting a distribution to the data. Therefore the AMS should be checked for the outliers before fitting it to a distribution. Outliers can be either low or high and both have different effects on the analysis. In this study, low outliers were removed from the AMS to avoid artificially low skewness in the 3-parameter distribution fitted to the annual maximum series and to avoid artificial high bias. However, considering the importance of higher peaks in FFA, it was decided not to remove the high outliers from the AMS. Ultimately a good quality streamflow data base for a total of 30 catchments was compiled for FFA in South Australia. Figure 1 illustrates the systematic process that is adopted in this to select suitable catchment and prepare good quality data series for FFA.

## 3. METHODOLOGY

The Probability Density Function (PDF) of the GEV distribution derived by Jenkinson (1955) is expressed as given in equation 1 and 2. The definitions of L moments as well as L moment ratios can be found in Hosking (1990). The ratio estimators of L moments namely, location, scale, and shape are nearly unbiased, regardless of the probability distribution from which the observations arise.

$$F(x)=\begin{cases}\exp\left(-\left[1-\frac{\kappa}{\alpha}(x-\xi)\right]^{\frac{1}{\kappa}}\right) & \kappa\neq 0\\ \exp\left(-\exp\left[1-\frac{1}{\alpha}(x-\xi)\right]\right) & \kappa=0\end{cases} \tag{1}$$

or in inverse form

$$x(F)=\begin{cases}\xi+\frac{\alpha}{\kappa}\left[1-(-\ln F)^{\kappa}\right] & \kappa\neq 0\\ \xi-\alpha\ln(-\ln F) & \kappa=0\end{cases} \tag{2}$$

where $\xi$ is the location parameter, $\alpha$ is a scale parameter and $\kappa$ is a shape parameter.

When the observed data do not follow a single trend, the selected probability model does not adequately fit the complete data series and low flows may exert undue influence on the fit and give insufficient weight to the higher flows which are the principal object of interest. To deal with this situation Wang (1997) introduced a generalization of L moments called LH moments, where it is called L1 moments, L2 moments,…for order ($\eta$) = 1,2,…respectively. When $\eta = 0$, LH moments become identical to L moments.

Trying to fit a single smooth function to the sample values can result in serious error in the quantile estimates at large return periods due to compromised position and shape of the curve (Wang 1997). Therefore, in fitting a distribution function to the observed data by L moments make an implicit and unrealistic assumption that the distribution function selected is appropriate for describing the full range of data. But with the LH moments, the emphasis can be given to the upper part of the distribution function. According to Wang (1997) this method diminishes the influence of small sample values when $\eta$ of the LH moments increases, because as $\eta$ increases, LH moments reflect more on the characteristics of the upper part of the distributions and large event in data. The definitions of LH moments as well as LH moment ratios can be found in Wang (1997) and the direct estimations of LH moments were calculated as described in the same study.

Three parameters ($\xi$ , $\alpha$ and $\kappa$) of the GEV distribution were estimated by matching the first three LH moments to their sample estimates for a selected $\eta$ using the equations given in Wang (1997). Once the parameters of the GEV distribution were calculated for different orders (L, L2 and L4) of LH moments, the quantiles at six selected Annual Recurrence Intervals (ARIs) (ARI =2, 5, 10, 20, 50 and100 years) were computed.

The performance of GEV/LH moments needs to be assessed to identify the best order of the LH moments for modelling floods in South Australia. Wang (1997) states that, although the true underlying distribution is never known in practice, it is still useful to look at how estimation is affected by various methods when the distribution function is known. This can be studied by fitting the GEV distribution function to generated GEV samples. Monte Carlo simulations were conducted for this purpose. In the Monte Carlo study, GEV was taken as the parent distribution and GEV samples of the same size as the observed were generated. For each of the 500 generated samples, GEV was fitted by LH moments of the same order that was used in fitting GEV to the observed series. Flood quantiles at the six selected recurrence intervals were then estimated for each of the 500 simulated samples. The simulated flood quantiles were then compared against the observed quantile at the respective ARI of interest by using Bias, MSE and efficiencies as discussed next.

### 3.1. Performance of the GEV/LH Moments

Assessment of the performance of the GEV distribution fitted by different orders of LH moments is essential for choosing the best order of LH moments for fitting GEV. This was assessed using a number of methods including probability plots, Bias, MSE and efficiency.

***Probability plots***

Although, probability plots alone are not adequate to differentiate between different distributions, they can be used to visualise the general trends of the observed data. In order to assess how well the proposed frequency distribution fits to the observed AMS, the plotting position is calculated as detailed below. The observed series was ranked in ascending order and non-exceedance probabilities were estimated using the Gringorton plotting position formula given in Equation 3 below.

$$F_i = \frac{i - 0.44}{n + 0.12} \tag{3}$$

where $n$ is the number of observations in the series, $i$ is the rank of a particular observation in the arranged series and $F_i$ is the plotting position of a particular observation. Flood quantiles at a given non-exceedance probability were estimated by fitting the GEV distribution using L moments, L2 moments and L4 moments. The probability plots for flood quantiles were then plotted against the different ARIs considered (2, 5, 10, 20, 50 and 100 year).

***Bias and Mean Square Error***

For each gauging site considered in this study, 500 flow series with similar record length as original were generated randomly. GEV distribution is then fitted to generated random samples using L, L2 and L4 moments. The flood quantiles at the six recurrence intervals were then computed and the selection of a particular order of LH moment for the GEV distribution was based on average Bias and MSE values computed using 500 simulated quantiles at each of the six selected ARIs. Bias and MSE were estimated using the following equations. To compare the performance of the different orders of LH moments, the efficiency ($\phi$) given by Equation 6 is used.

$$BIAS(\hat{\theta}) = E(\hat{\theta} - \theta) \tag{4}$$

$$MSE = E\left[(\hat{\theta} - \theta)^2\right] = \left[BIAS(\hat{\theta})\right]^2 + \mathbf{var}(\hat{\theta}) \tag{5}$$

$$\phi = \frac{MSE_{L\,moment}}{MSE_{L2\,moment}} \tag{6}$$

## 4. RESULTS AND DISCUSSION

### 4.1. Probability plots

Probability plots were used to compare GEV fits for different orders of LH moments. Three shapes of frequency curves; straight, convex and concave were observed for the region as can be seen in Figures 2. It was also observed that GEV/L moments fit the observed (OBS) data well at lower ARIs, but as the ARI increases, the distribution deviates from the observed flood data. The GEV/ L moment curve shows the highest deviation where as GEV/ L4 is the least deviated fit at the upper tail although this was not clearly distinguished in probability plots. However, these GEV/LH plots do not clearly demarcate the best fitting order of LH moments and hence it is difficult to draw any objective conclusion on choosing the most

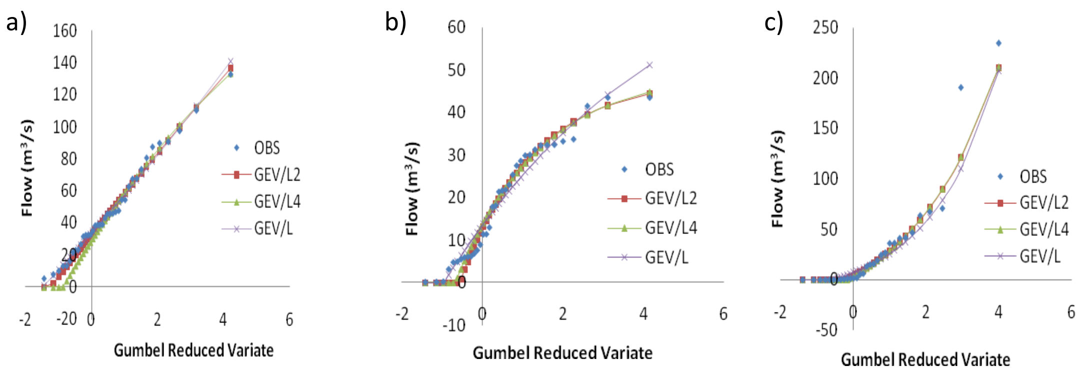


**Figure 2: a)** Straight shape of probability plot for station A4260504 **b)** Convex shape of probability plot for station A5070500 **c)** Concave shape of probability plot for station A4260536

appropriate order of the LH moment by using these probability plots. This was a common issue at majority of the catchments.

### 4.2 Comparing Bias and Efficiency at different orders of LH moments

The results of the Monte Carlo simulation conducted for station A5040525 are presented in Figure 3 for demonstration purposes. In Figure 3 (a), it can be observed that as the ARI increases, Bias of L2 moments estimates and L4 moments estimates consistently decreased while that of the L moments is increased. Overall, L4 moments estimates are with the least Bias at ARIs over 10 years. The quantiles made using the L moments and L2 moments show smaller Bias at smaller recurrence intervals (ARI = 2 and 5 year). It is observed from Figure 3 (b) that at 10 year ARI, L4 moments method indicate very high efficiency relative to the L2 moments method. This observation was made at majority of the stations where Bias is much closer to zero. Although the efficiency of L4 moments method in Figure 3 (b) is slightly less with the increase of ARIs, overall L4 moments are more efficient than L2 moments.

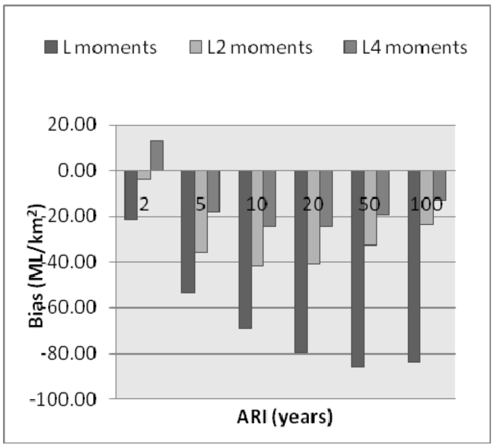


**Figure 3 (a).** Bias of station A5040525

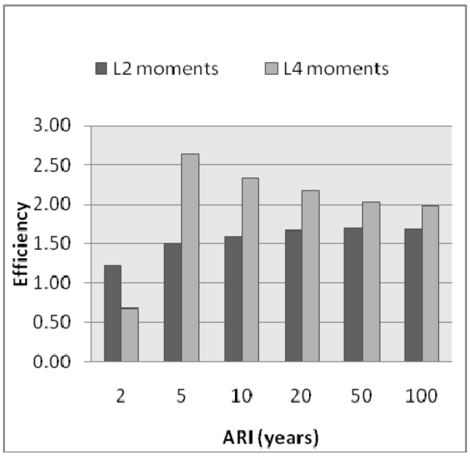


**Figure 3 (b).** Efficiency of station A5040525

Bias and Efficiency estimates of the 30 selected catchments are summarised using box-plots as shown in Figure 4 and Figure 5. The L4 moments estimates have the least Bias at every ARI except ARI= 2 year where L2 moments estimate has the least Bias. This can be observed through both the median of the box plot and the dispersion. However, it is not justifiable to draw any objective conclusion merely on Bias alone. Therefore, the Efficiencies of the LH moments of these three orders need to be assessed and compared.

In order to get a clear picture of the overall trend of the efficiency, a box plot is drawn as shown in Figure 5. The median efficiencies of the both L2 moments and L4 moments are less than 1 at the 2 year ARI. This observation suggests that at the 2 year ARI, L moments are better than the other two methods. However, in flood frequency analysis our interest is basically focused on higher ARIs and

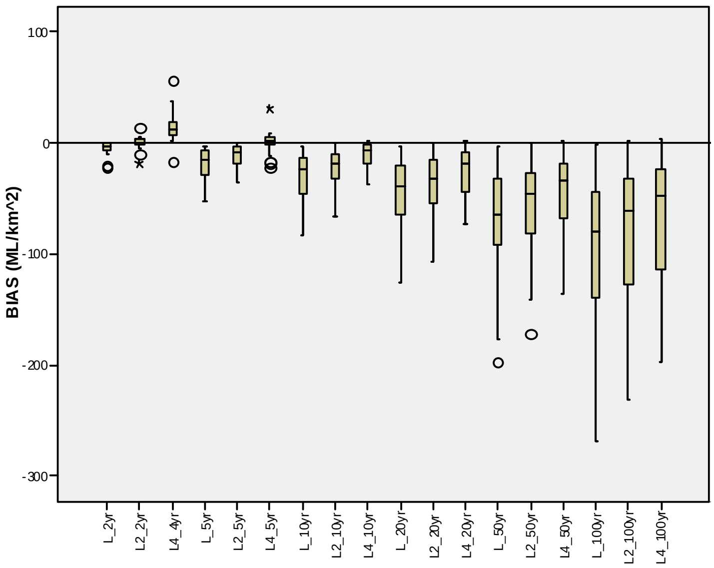


**Figure 4.** Summary box plot of Bias for L, L2 and L4 moments for the South Australian catchments considered

it is clear that L4 moments are superior to L moments or L2 moments in terms of both Bias and efficiency. Wang (1997) pointed out some disadvantages associate with higher order LH moments. According to Wang (1997), higher order LH moments will discard the values in the lower tail of the sample distribution and will cause high sampling variability. However, as mentioned in introduction some researchers state that suitable order of LH moment is site specific and L2 moments would not always be the best estimator.

In summary the results of the present study show that L4 moments outperform L2 and L moments for the quantile estimates of interest. Therefore, GEV/L4 moments method was selected for making reliable at-site flood quantile estimates for the study area.

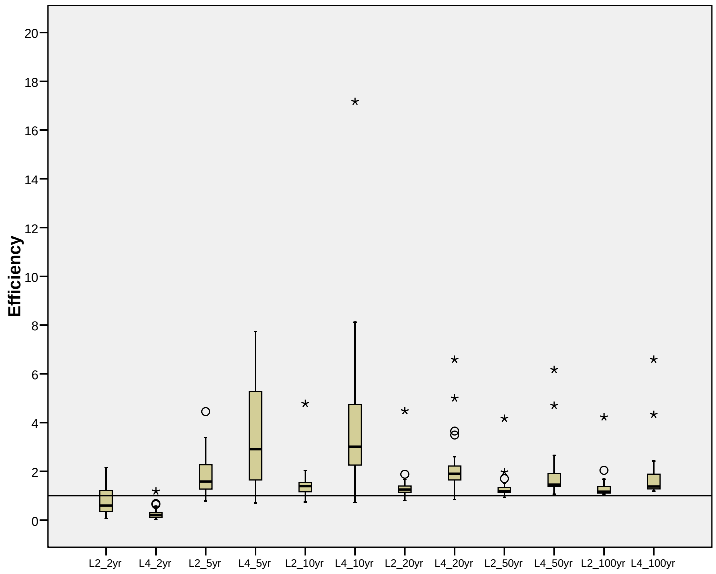


**Figure 5:** Summary box plot of Efficiency for L2 and L4 moments with respect to L moments for the South Australian catchments considered

## 5. CONCLUSION

This paper details the modelling of extreme flood events in South Australian catchments. The reliability of predictions through RFFA largely depends on the quality and representativeness of flood observations at the gauged stations. Therefore, in this study the selection and preparation of data have been done in a way that it will maximize the amount of useful flood information, while minimising the errors associate with it. The best order of the LH moments to fit GEV distribution for modelling floods in South Australia has been identified. Monte Carlo simulations were conducted to assess the performance of the different orders of LH moments. Comparing Bias and Efficiency of the quantiles made by fitting GEV using L, L2 and L4 moments, it was discovered that L4 moments was the best out of the three orders and hence, GEV distribution fitted by L4 moments is recommended as the best approach for at-site FFA in South Australia.

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