COMPARISON BETWEEN ANNUAL MAXIMUM AND PEAKS OVER THRESHOLD MODELS FOR FLOOD FREQUENCY PREDICTION

Mkhandi S.¹, Opere A.O.², Willems P.³

¹ University of Dar es Salaam, Dar es Salaam, 25522, Tanzania, s_mkhandi@yahoo.com
² Department of Meteorology, University of Nairobi, Nairobi, 00100 (GPO), Kenya, aopere@uonbi.ac.ke
³ Hydraulics Laboratory, K.U.Leuven, Leuven, B-3001, Belgium, Patrick.Willems@bwk.kuleuven.ac.be

ABSTRACT

The estimation of flood magnitudes required for the design of hydraulic structures can be achieved by making use of two types of flood peak series, namely Annual Maximum (AM) series and Peaks over Threshold (PoT). The dilemma in flood frequency analysis therefore is on whether to use AM series or PoT series. In this study a comparison is made in using AM and PoT series to estimate flood magnitudes in the Equatorial Lake Victoria subbasin upstream in the Nile basin. The technique based on regression in Q-Q plots (QQR method), only recently introduced in hydrology, is used to evaluate the applicability of the extreme value distributions to model the AM and PoT series. The QQR method allows to do the evaluation by analyzing the shape of the tail of the distribution of extreme events. The discrimination between heavy tail, normal tail and light tail cases, facilitates inference on the suitable distribution to model the extreme events. The data used in the study is from three gauging stations located in the Equatorial Lake Victoria subbasin on the Kenyan side. The evaluation of the applicability of the extreme value theory for at site AM and PoT series for the stations considered in the study on the basis of the exponential Q-Q plot inferred that Extreme value type 1(EV1) and Exponential (EXP) distributions are suitable to model the AM and PoT extreme events respectively. Comparison of empirical and theoretical distributions fitted to the AM and PoT extreme events indicated that at higher return periods (greater than 10 years), both AM and PoT models give similar or comparable predictions of flood magnitudes.
INTRODUCTION

Flood frequency analysis plays a major role in the design of hydraulic structures such as bridges, culverts, reservoir spillways and flood control levees. The constructions of the mentioned structures are governed by the flood magnitude. Estimation of flood magnitudes to be used as a basis to design the hydraulic structures is therefore of crucial importance.

One way of estimating the design flood is by performing frequency analysis of observed flood peaks over a number of years at the site of interest. The main objective of flood frequency analysis therefore is to establish a relationship between flood magnitude (Q) and recurrence interval or return period (T).

The estimation of flood magnitudes can be achieved by making use of two types of flood peak series, namely Annual Maximum (AM) series and Peaks over Threshold (PoT) (e.g. Hosking & Wallis, 1987; Madsen et al., 1997). The AM series consists of one value, the maximum peak flow, from each year of record while the PoT series consists of all well defined peaks above a specified threshold value. Each model attempts to represent the flood peak aspects of the entire series of flow hydrographs by a simple series of flood peak values. PoT series are also denoted by some authors as Partial Duration Series (PDS) because the flood peaks can be considered as the maximum flow values during hydrograph periods of variable length. The periods divide the full flow record in subseries with partial durations (Rosbjerg et al., 1992).

The dilemma in flood frequency analysis is whether to use AM series or PoT series. The most frequent objection encountered with respect to the use of AM series is that it uses only one flood for each year. In some cases, the second largest flood in a year which the AM series neglects may be greater than many AM floods of other years. Another shortcoming of AM series is that only a small number of flood peaks is considered. On the other hand, the PoT series appears to be more useful for flood frequency analysis than AM series, since the objections raised on AM series do not apply. The major drawback of PoT series is that flood peaks might not form an independent time series since some flood peaks may occur on the recession curves of the preceding flood peaks. The dependence between the PoT or PDS values is a function of the hydrological independence criterion used to divide the full series in its partial durations or of the parameters (e.g. threshold level) used to define the particular PoT values (e.g. Lang et al., 1999). In this study a comparison is made in using AM and PoT series to estimate flood magnitudes in the Equatorial Lake Victoria subbasin.

STATISTICAL MODELING OF AM AND PoT SERIES

ANNUAL MAXIMUM SERIES MODEL

The AM series model replaces the flow series for each year by its largest flood. The series \( q_1, q_2, q_3, \ldots, q_n \) where \( q_j \) is the maximum flood occurring in the \( j \)th year, is the random sample from some underlying population. The distribution of the flood magnitudes, \( q_j \), statistically can be determined by making use of the theory of extreme value statistics invoked by Gumbel. He asserted that AM series come from the family of extreme value distributions referred to as Generalized Extreme Value (GEV) distributions.

The cumulative probability function (CDF) for the GEV distributions is given by:
where \( u, \alpha \) and \( k \) are location, scale and shape parameters respectively. In the case \( k=0 \), the distribution matches the Extreme Value type 1 (EV1) or Gumbel distribution.

The inverse distributions are given by:

\[
q = u + \frac{\alpha}{k} \left\{ 1 - \left( -\ln(F(q)) \right)^k \right\} \quad \text{for } k \neq 0 \\
q = u + \alpha \left( -\ln - \ln F(q) \right) \quad \text{for } k = 0
\]

where \( F(q) = \Pr (Q \leq q) \). The return period of recurrence interval (in years) is calculated by the inverse of the survival function (the inverse of \( 1-F(q) \)):

\[
T = \frac{1}{1 - F(q)}
\]

**PEAKS OVER THRESHOLD SERIES MODEL**

The PoT series model replaces the continuous hydrograph of flows by a series of randomly spaced spikes on the time axis. If \( ?t \) is the average time between peaks, then, \( 1/?t = \lambda \), is the average number of peaks per unit of time. The peaks are considered to be statistically independent. Selection of the peaks from the time series can be done using different methods. In this study, the method proposed by Willems (2003, 2005) is used where two adjacent peaks are considered independent if:

(i) the time between the two peaks is longer than the recession constant of the quick flow runoff components for the given catchment;

(ii) the minimum discharge between the two peaks is smaller than 37\% of the peak discharge.

In order to avoid that smaller peak heights are selected a minimum threshold value is determined.

The distribution of the PoT series, \( q_j \), statistically can be determined by making use of the Generalized Pareto Distribution (GPD) as proposed by Pickands (1975). The cumulative probability function (CDF) for the Generalized Pareto Distribution is given by:

\[
F(q) = 1 - \left( 1 + \frac{q - q_0}{\beta} \right)^{-\frac{1}{k}} \quad \text{for } k \neq 0
\]

\[
F(q) = 1 - \exp\left( -\frac{q - q_0}{\beta} \right) \quad \text{for } k = 0
\]

In the case \( k=0 \), this distribution matches the exponential (EXP) distribution (with threshold \( q_0 \)).
The inverse distributions are given by:

\[
\ln(q) = \ln(q_0) + k(\ln(T) - \ln(\frac{n}{t})) \quad \text{for } k \neq 0 \tag{8}
\]

\[
q = q_0 + \beta(\ln T - \ln(\frac{n}{t})) \quad \text{for } k = 0 \tag{9}
\]

where \(q_0, \beta, \) and \(\gamma\) are the location, scale and shape parameters respectively; \(n\) equals the number of years and \(t\) the rank of threshold value (empirical number of selected peaks above the threshold \(q_0\)). \(T\) is the return period, which in case of PoT extremes is to be calculated from the survival function by:

\[
T = \frac{n}{t(1 - F(x))} \tag{10}
\]

**SELECTION OF DISTRIBUTION TO MODEL AM AND PoT SERIES**

The selection of a distribution to model extreme events for a particular site or region can be made by applying various goodness-of-fit tests, i.e., Chi-square, Kolmogorov-Smirnov, moment ratio diagram, regional behavior of statistics and quantile-quantile (Q-Q) plots. In this study the Q-Q plot techniques as proposed by Beirlant et al (1996) for insurance extreme value analysis, and demonstrated by Willems (1998) for hydrological applications, were used to evaluate the applicability of the extreme value distributions to model the AM and PoT series. Three types of Q-Q plots, namely Exponential Q-Q, Pareto Q-Q, and Generalized Q-Q or UH plots are applicable in the evaluation. On the basis of these plots an analysis on the shape of the tail of the distribution of extreme events is conducted and discrimination made between heavy tail, normal tail and light tail behavior. The visual interpretations to be made in the Q-Q plots are summarized in Table 1. They are based on the asymptotic tail properties towards the higher observations.

Table (1): Discrimination between heavy, normal and light tails behavior based on Q-Q plots

<table>
<thead>
<tr>
<th>Plot type</th>
<th>Normal</th>
<th>Tail type</th>
<th>Light</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential Q-Q</td>
<td>The upper tail points tend towards a straight line</td>
<td>The upper tail points continuously bend up</td>
<td>The upper tail points continuously bend down</td>
</tr>
<tr>
<td>Pareto Q-Q</td>
<td>The upper tail points continuously bend down</td>
<td>The upper tail points tend towards a straight line</td>
<td>The upper tail points also continuously bend down</td>
</tr>
<tr>
<td>UH</td>
<td>The slope in the upper tail approaches the zero value</td>
<td>The slope in the upper tail is systematically positive</td>
<td>The slope in the upper tail is systematically negative</td>
</tr>
</tbody>
</table>
The results of the analysis in the Q-Q plots are used to infer the distribution which can be used to model the extreme value events being considered, i.e., AM or PoT. In most cases, the candidate distributions for AM series are GEV and EV1 of which in the Exponential Q-Q plot, the GEV distribution would be depicted by the upper tail points continuously bending up (i.e., characterizing a heavy tail) or the upper tail points continuously bending down (i.e., characterizing a light tail), while EV1 distribution would be depicted by the upper tail points tending towards a straight line (i.e., characterizing a normal tail). On the other hand, the candidate distributions for PoT series are GPD and EXP of which in the Exponential Q-Q plot, the GPD distribution would be depicted by the upper tail points continuously bending up (i.e., characterizing a heavy tail) or the upper tail points continuously bend down (i.e., characterizing a light tail), while EXP distribution would be depicted by the upper tail points tending towards a straight line (i.e., characterizing a normal tail).

**CALIBRATION OF DISTRIBUTION PARAMETERS**

The parameters of the frequency distribution are estimated from the sample data. Since the sample data is subject to error, the method of estimating the parameters must be efficient. The distribution parameters can be estimated by either the Method of Moments (MOM), the Maximum Likelihood (ML) method or the Method of Probability Weighted Moments (PWM). The method of moments is one of the most commonly and simply used method for estimating parameters of a statistical distribution. In most cases the first three central moments are required to estimate the parameters, i.e. mean, variance and skewness. The method of maximum likelihood is not commonly used due to the complexity involved in deriving the parameters by this method. The Probability Weighted Moments which were introduced by Greenwood et al (1979) and further analyzed by Hosking (1986), were originally proposed for the distributions whose inverse form can be explicitly defined, such as EV1 and GEV. The PWM method has come to be regarded as one of the best methods for parameter estimation by research hydrologists according to Hosking (1985) and has gained greater recognition in flood frequency analysis than other methods according to Cunnane (1989). However, in the environment where the distribution gives a linear plot, like in the case of GPD distribution which appears linear in the exponential Q-Q plot (for the normal tail case) and in the Pareto Q-Q plot (for the heavy tail case), calibration of the distribution can be done by regression in the Q-Q plot whereby the inverse slope in the Q-Q plot equals the $\beta$ parameter in case of the exponential Q-Q plot and the $k$ index in case of the Pareto Q-Q plot. The optimal threshold $q_0$ above which regression is conducted is selected as the point where the Mean Squared Error (MSE) of the regression is minimum in the range where the slope estimates are stable with small variance. This method where parameter estimation is done based on regression in Q-Q plots is hereafter shortly denoted as the “QQR method”. However, for certain parameter combinations in the GPD case, and for the GEV distribution, the distribution does not appear linear for their full range of flow values. The linear shape is in these cases guaranteed only asymptotically towards the higher extremes (asymptotic convergence to a constant slope) in the Q-Q plot. By regression in the Q-Q plot (QQR method) asymptotic slope estimates still can be made in these cases.

**DATA**

The data used in the study was from three gauging station located in the Equatorial Lake Victoria subbasin located on the Kenyan side. The overview of the gauging stations used in the study is presented in Table 2. From the Table, it can be observed that streamflow records were available for the period from 1947 to 1994 and the record length of available continuous data
varies from 15 to 21 years. The data from those years with continuous records only were used in
the analysis. The data from the gauging stations on the Tanzanian side were not considered in
the analysis because they were of short record length less than 11 years.

Table (2): Selected stations in Lake Victoria subbasin used in the study

<table>
<thead>
<tr>
<th>Serial No.</th>
<th>River</th>
<th>Station</th>
<th>Location</th>
<th>Period of record</th>
<th>No. of years record with continuous data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Nzoia</td>
<td>1EE01</td>
<td>0.178</td>
<td>1964-1984</td>
<td>15</td>
</tr>
<tr>
<td>2</td>
<td>Sondu</td>
<td>1JG01</td>
<td>-0.393</td>
<td>1947-1988</td>
<td>21</td>
</tr>
<tr>
<td>3</td>
<td>Nyando</td>
<td>1GD03</td>
<td>-0.125</td>
<td>1970-1994</td>
<td>19</td>
</tr>
</tbody>
</table>

The data that was of relevance to the study was the extreme flow series. As such, AM and
PoT series were extracted from the daily streamflow records for the three gauging stations
considered in the study. The PoT values were extracted by using the WETSPRO software,
which has been developed by the Hydraulics Laboratory of K.U.Leuven in Belgium. The
software extracts nearly independent PoT extremes from the flow series by applying the
criteria mentioned earlier. The example of the extracted AM and PoT values for one of the
stations used in the study (Nzoia at 1EE01) for the period 1980 to 1984 is shown in Figure 1.
The statistics of the extracted extreme events are presented in Table 2. From that table it can
be observed that the coefficient of variation for both AM and PoT are comparable in that the
values range between 0.4 and 0.6. The values of the coefficient of skewness range from 0.2 to
1.2 and 1.1 and 2.0 for AM and PoT respectively.

Table (3): Statistics of extreme events extracted from flow records

<table>
<thead>
<tr>
<th>Serial No.</th>
<th>River</th>
<th>Station</th>
<th>Catchment area Km²</th>
<th>Mean Annual Flood</th>
<th>Coeff. of Variation</th>
<th>Coeff. of Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AM Flow Series</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Nzoia</td>
<td>1EE01</td>
<td>11849</td>
<td>310.46</td>
<td>0.42</td>
<td>0.23</td>
</tr>
<tr>
<td>2</td>
<td>Sondu</td>
<td>1JG01</td>
<td>3287</td>
<td>199.52</td>
<td>0.55</td>
<td>1.21</td>
</tr>
<tr>
<td>3</td>
<td>Nyando</td>
<td>1GD03</td>
<td>2625</td>
<td>156.07</td>
<td>0.56</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>PoT Flow Series</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Nzoia</td>
<td>1EE01</td>
<td>11849</td>
<td>254.83</td>
<td>0.39</td>
<td>1.08</td>
</tr>
<tr>
<td>2</td>
<td>Sondu</td>
<td>1JG01</td>
<td>3287</td>
<td>193.62</td>
<td>0.47</td>
<td>1.74</td>
</tr>
<tr>
<td>3</td>
<td>Nyando</td>
<td>1GD03</td>
<td>2625</td>
<td>146.10</td>
<td>0.45</td>
<td>2.04</td>
</tr>
</tbody>
</table>
THE ANALYSIS OF THE SHAPE OF THE UPPER TAIL OF THE DISTRIBUTION OF THE EXTREME EVENTS

As explained in the earlier section the AM and PoT data for the three stations were subjected to the Q-Q plots to evaluate the applicability of the extreme value theory. This was followed by carrying out the analysis of the shape of the tail of the distribution of extreme events. From this analysis, discrimination between heavy tail, normal tail and light tail behaviour was made. The examples of the evaluation of the extreme value distribution using the Exponential Q-Q plot are shown in Figure 2 (example for AM) and Figure 3 (example for PoT).

The results of the exponential Q-Q plots for all the three stations i.e., Nzoia at 1EE01, Sondu at 1JG01 and Nyando at 1GD01 suggest a normal tail distribution in that the plots of the upper tail points tend towards a straight line. On the basis of the results of the analysis of the shape of the upper tail, EV1 distribution was inferred as the suitable distribution to model the AM series (a special case of GEV for $k=0$ while EXP distribution was inferred as the suitable distribution to model PoT series (a special case of GPD for $k=0$).
Figure (2): Exponential Q-Q plot for AM for Nzoia at 1EE01

Figure (3): Exponential Q-Q plot for PoT for Nzoia at 1EE01
COMPARISON BETWEEN AM AND PoT MODELS

COMPARISON BETWEEN EMPIRICAL AND THEORETICAL DISTRIBUTIONS OF AM AND PoT MODELS

The observations in Figures 4 and 5 represent the empirical distributions. For the case of the AM series, the cumulative probability as well as the exceedance probability \((1-F)\) were computed by using the Gringorten formula given as:

\[
F_i = \frac{N - i + 0.44}{N + 0.12}
\]

(11)

where \(i, N, F_i\) are the rank of extreme event (1 for the highest event, 2 for the second highest, etc.), the number of extreme events and the non-exceedance probability respectively.

For the PoT extreme events, the Weibull formula was selected:

\[
F_i = \frac{N - i + 1}{N + 1}
\]

(12)

Following the selection of the distributions to model the AM and PoT series for the stations analyzed, theoretical distributions were fitted to the empirical data. The AM series was fitted to the EV1 distribution by calibrating the parameters of the distribution by the PWM method and the asymptotic slope property tested by regression in the exponential Q-Q plot as described earlier. The PoT series was fitted to the EXP distribution by calibrating the parameters of the distribution by regression in the exponential Q-Q plot (QQR method).

For comparison purposes, the empirical and theoretical distributions fitted to the AM and PoT extreme events were plotted on the same scale for each of the station analysed. From the plotted figures, it is observed that the empirical and theoretical distributions for AM and PoT extreme events tend to converge at higher return periods, giving the indication that at higher return periods (greater than 10 years), both AM and PoT models would give similar or comparable predictions of flood magnitudes. This also has been proven in a theoretical way by Langbein (1947) and Chow et al. (1988). Under the assumption of independent PoT extremes distributed in time according to a Poisson process (exponential inter-event times with rate \(\lambda\), as described in the earlier section) it indeed can be easily derived from Equations (5) and (10) that the following relationship exist between the return period derived from AM extreme value analysis \((T_{AM})\) and the return period derived from PoT analysis \((T_{PoT})\):

\[
\frac{1}{T_{AM}} = 1 - \exp\left(-\frac{1}{T_{PoT}}\right)
\]

(13)

Based on this equation, is it seen that the differences between \(T_{AM}\) and \(T_{PoT}\) can be neglected for \(T>10\) years. For lower \(T\), the AM based \(T\) is lower than the PoT based \(T\). This is due to the fact that the AM series only consider the highest values in any year, and consequently might miss some significant peak flow values (classified as second, third, or … highest value
in the year). The difference between $T_{AM}$ and $T_{PoT}$ therefore can be seen as an underestimation of the AM based approach in comparison with the PoT based analysis.

Examples of the plots are shown in Figure 4 (example for Nzoia at 1EE01) and Figure 5 (example for Sondu at 1JG01). From Figure 4, the convergence of $T_{AM}$ towards $T_{PoT}$ is clearly observed, as well as the convergence of both distributions towards the same constant slope in the exponential Q-Q plot (normal tail case). Figure 5 shows similar trends as for Figure 4. The differences between the AM and PoT based distributions is explained by the difference in approach (AM give underestimations of the return period estimations for return periods lower than 10 years, in comparison with the PoT based approach; see Equation (13)), as well as differences in the calibration method and randomness/uncertainty in the calibrations.

Figure (4): Comparison between empirical and theoretical distributions of PoT and AM series for Nzoia at 1EE01
Figure (5): Comparison between empirical and theoretical distributions of PoT and AM series for Nsondu at 1JG01

OVERVIEW OF DISTRIBUTION PARAMETERS

The results presented in the above section suggest the selection of the EV1 and EXP distributions as suitable distributions to model the AM and PoT extreme events respectively in the Equatorial Lake Victoria subbasin on the basis of the exponential Q-Q plot. The calibrated parameters for the EV1 distribution by using the PWM method ($\mu$ and $\alpha$) and the QQR method (threshold rank $t$, $k$, $\beta$, and threshold level $q_0$) for the 3 sites are presented in Table 4. The calibrated parameters for the EXP distribution by regression in the exponential Q-Q are presented in Table 5.

Table (4) (a): Calibrated parameters for EV1 by PWM for the AM series

<table>
<thead>
<tr>
<th>Station</th>
<th>PWM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$q_0$</td>
</tr>
<tr>
<td>Nzoia at 1EE01</td>
<td>247.00</td>
</tr>
<tr>
<td>Sondu at 1JG01</td>
<td>149.00</td>
</tr>
<tr>
<td>Nyando at 1GD03</td>
<td>117.72</td>
</tr>
</tbody>
</table>

Table (4) (b): Calibrated parameters for EV1 by QQR for the AM series

<table>
<thead>
<tr>
<th>Station</th>
<th>Regression parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Threshold rank ($t$)</td>
</tr>
<tr>
<td>Nzoia at 1EE01</td>
<td>13</td>
</tr>
<tr>
<td>Sondu at 1JG01</td>
<td>19</td>
</tr>
<tr>
<td>Nyando at 1GD03</td>
<td>16</td>
</tr>
</tbody>
</table>
Table (5): Calibrated parameters for the EXP distribution by QQR for the PoT series

<table>
<thead>
<tr>
<th>Station</th>
<th>Regression parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of years of record</td>
</tr>
<tr>
<td>Nzoia at 1EE01</td>
<td>15</td>
</tr>
<tr>
<td>Sondu at 1JG01</td>
<td>21</td>
</tr>
<tr>
<td>Nyando at 1GD03</td>
<td>19</td>
</tr>
</tbody>
</table>

**COMPARISON OF FLOOD MAGNITUDES ESTIMATED USING AM AND PoT MODELS**

The fitted EV1 and EXP parameters by PWM and QQR respectively were used to estimate flood magnitudes for the return periods 5, 10, 20, 50, 100 and 200 years. The results for the three stations are presented in Table 6.

Table (6): Peak flow magnitudes estimated from AM series and PoT series

<table>
<thead>
<tr>
<th>Return Period</th>
<th>Nzoia at 1EE01</th>
<th>Sondu at 1JG01</th>
<th>Nyando at 1GD03</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years</td>
<td>Q-T&lt;sub&gt;PoT&lt;/sub&gt;</td>
<td>Q-T&lt;sub&gt;AM&lt;/sub&gt;</td>
<td>Q-T&lt;sub&gt;PoT&lt;/sub&gt;</td>
</tr>
<tr>
<td>5</td>
<td>455</td>
<td>412</td>
<td>455</td>
</tr>
<tr>
<td>10</td>
<td>528</td>
<td>494</td>
<td>528</td>
</tr>
<tr>
<td>20</td>
<td>601</td>
<td>574</td>
<td>601</td>
</tr>
<tr>
<td>50</td>
<td>698</td>
<td>676</td>
<td>698</td>
</tr>
<tr>
<td>100</td>
<td>771</td>
<td>753</td>
<td>771</td>
</tr>
<tr>
<td>200</td>
<td>844</td>
<td>829</td>
<td>844</td>
</tr>
</tbody>
</table>

In order to make comparison between the flood magnitudes estimated using the fitted EV1/AM model and the fitted EXP/PoT model the estimated values were plotted on a scatter diagram for the three stations. The scatter plots are shown on Figure 6. From these plots it is observed that the PoT model give higher flood estimates for two stations, Nzoia at 1EE01 and Sondu at 1JG01, and lower values for the station Nyando at 1GD03. However, the estimated values are fairly close.

**CONCLUSIONS**

The evaluation of the applicability of the extreme value theory for at site AM and PoT series for the stations considered in the study on the basis of the exponential Q-Q plot inferred that the EV1 distribution and the EXP distribution are suitable to model the AM and PoT extreme events respectively in Equatorial Lake -Victoria subbasin. Both models are normal tail distributions.

Comparison of empirical and theoretical distributions fitted to the AM and PoT extreme events have indicated that at higher return periods (greater than 10 years), both AM and PoT models give similar or comparable predictions of flood magnitudes.
Figure (6): Comparison between flood magnitudes estimated using AM and those estimated using PoT
Acknowledgments

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