Statistical Analysis of Annual Maximum Rainfall Data of North-East India Based on the Methods of TL-Moment

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Research Article

Abstract: This paper aims to demonstrate the application of the method of Trimmed L-moment (TL-moment) to determine the best fitting distribution for annual series of maximum daily rainfall data of nine distantly located stations of North East India. For this purpose, three extreme value distributions viz. Generalized Extreme Value distribution (GEV), Generalized Logistic distribution (GLD), Generalized Pareto distribution (GPD) are considered and the parameters for each of the aforesaid distributions are estimated using the method of TL-moment. The performances of the distributions are evaluated using three goodness of fit tests namely relative root mean square error, relative mean absolute error and probability plot correlation coefficient. Finally, goodness of fit test results are compared and generalized extreme value distribution is empirically proved to be the most appropriate distribution for describing the annual maximum rainfall data for all the stations considered when the parameters are estimated by using TL-moment method.

Key Words: TL-moments, Extreme value distribution, Quantile function, North East India.

1. Introduction

The severity of the weather, which manifest in the form of floods and landslides on account of rainfall, has a substantial impact on the life and properties. In recent years, heavy rainfall event have resulted in several disparaging floods in North East India. It causes immense destruction of crops, property and even of life in the region. Information on extreme rainfall magnitude and their frequencies are needed for hydrological planning, designing and operation of water resources development programmes. In the present study, an attempt has been made to analyze the statistical modeling of extreme rainfall data using Trimmed L-moment (TL-moment). Elamir and Seheult (2003) developed the TL-moments as a generalization of the L-moments with more advantages over L-moments and conventional moments. TL-moments assign zero weight to extreme observations, they are easy to compute and more robust than L-moments when used to estimate from a sample containing outliers. TL-moments exist even if the distribution does not have a mean. For example, existence of TL-moments for Cauchy distribution. A few studies have been carried out dealing with applications of TL-moments method; see Hosking (2007), Asquith (2007), Moneiem (2007), Moniem and Selim (2009), Noura *et al*. (2010). We now give a brief account of literature on extreme value distributions. The most commonly used distributions for extreme events can be found from the references such as Hosking and Wallis (1997) and Rao and Hamed (2000). Since then extreme value distributions to rainfall data have been investigated by several authors from different region of the world. Extreme value distributions have also been used by Aronica *et al*. (2002) to analyze the trend in the extreme rainfall series for a fixed return period by estimating the maximum rainfall depth in Palermo, Sicily, Italy. They estimated the parameters using Lmoments. Zalina *et al*. (2002) discussed the comparative assessment of eight candidate distributions in providing accurate and reliable maximum rainfall estimates for Malaysia. Model parameters were estimated using the L-moment method. They concluded that the GEV distribution is the most appropriate distribution for describing the annual maximum rainfall series in Malaysia. On the other hand, Zin *et al*. (2008) found GLD as the most frequently selected best fitting distribution and lognormal (LN3) distribution as the least frequently selected distribution for extreme rainfall in Peninsular Malaysia. Those results differ from the results obtained by Zalina *et al*. in Zalina *et al*. (2002). Recently, Deka *et al*. (2010, 2011) has found generalized logistic distribution (generalized Pareto distribution) as the most appropriate distribution for describing the annual maximum rainfall series for the majority of the stations in North East India using LQ moments (LH moments). Although a good number of articles are devoted to the statistical modeling of extreme rainfall using L-moments, LQ-moments and LH-moments, there are few literatures concerning the use of TL-moments in the statistical modeling of extreme rainfall. For this purpose, three 3-parameter extreme value distributions viz. Generalized Extreme Value distribution (GEV), Generalized Logistic distribution

(GLD), Generalized Pareto distribution (GPD) are considered. The estimation of the parameters for each distribution has been done using the methods of TL-moment.

2. Data and Methodology

Series of annual maximum daily rainfall data of nine stations in North East India viz Imphal, Mohanbari, Guwahati, Cherrapunji, Pasighat, North Lakhimpur,Silchar, Shillong, and Tezpur for a period of 42 years from 1966 to 2007 have been considered for this study.The geographical locations of the nine rain gauge stations are shown in Fig. 1. The series of block maxima for annual blocks of daily rainfall data of the aforesaid stations are collected from Regional Meteorological Centre, Guwahati. The set of daily rainfall data is complete for the analysis period.

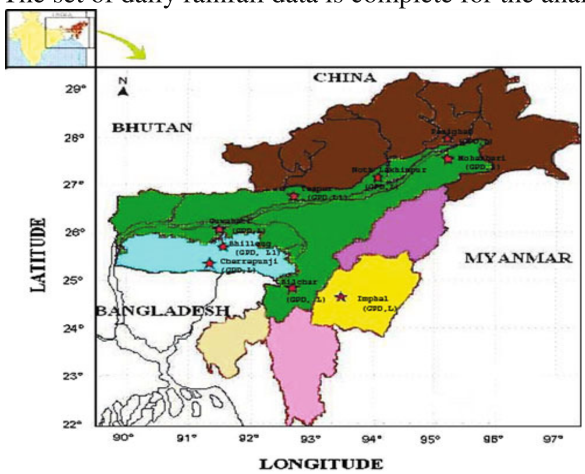

Figure 1: Location of rain gauge stations used in this study

The behavior of extreme rainfall at a particular area can be described by identifying the best fitting distribution and the performance of a particular distribution depends on the method of the estimation of the parameters. The good estimator of the parameters may be obtained by selecting the proper method of estimation. In this study, the parameters for each of the aforesaid distributions are estimated using the method of TL-Moment.

2.1 Method of Tl-Moment

The fundamental steps of TL-moments are essentially the same as L-moments. Let $X_1, X_2, \ldots, X_n$ be a sample from a continuous distribution function F(.) with quantile function Q(F) and let $X_{1:n} \le X_{2:n} \le \ldots \le X_{n:n}$ denotes the order statistics. Then the r^th L-moment λ_r is given by

$$\lambda_r = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} E(X_{r-k:r}), \quad r = 1,2,\ldots. \tag{1}$$

In TL-moments defined by Elamir *et al*. (2003), the expectations term $E(X_{r-k:r})$ in Eq.(1) will be replaced by $E(X_{r+t_1-k:r+t_1+t_2})$. That is, for each r, the conceptual sample size will be increased from r to $r + t_1 + t_2$ and work only with the expectations of the r order statistics $Y_{t_1+1:r+t_1+t_2}, \ldots, Y_{t_1-r:r+t_1+t_2}$ by trimming the t_1 smallest and t_2 largest from the conceptual sample. Thus the rth TL-moment $\lambda_r^{(t_1,t_2)}$ is defined as

$$\lambda_r^{(t_1,t_2)} = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} E(X_{r+t_1-k:r+t_1+t_2}), \quad r = 1,2,\ldots.$$

For $t_1 = t_2 = 0$, TL-moments yields the original L-moments and when $t_1 = t_2 = t$, then the r^th TL moment is defined as

$$\lambda_r^{(t)} = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} E(X_{r+t-k:r+2t}), \quad r = 1,2,\ldots.$$

In our study, we have considered TL-moments for t=1to estimate the parameters of each of the aforesaid distributions. When t=1the first four TL-moments can be expressed as

$$\lambda_1^{(1)} = E[X_{2:3}] = 6\beta_1 - 6\beta_2,$$
$$\lambda_2^{(1)} = \frac{1}{2}E[X_{3:4} - X_{2:4}] = 6(-2\beta_3 + 3\beta_2 - \beta_1),$$
$$\lambda_3^{(1)} = \frac{1}{3}E[X_{4:5} - 2X_{3:5} + X_{2:5}] = \frac{20}{3}(-5\beta_4 + 10\beta_3 - 6\beta_2 + \beta)_1,$$
$$\lambda_4^{(1)} = \frac{1}{4}E[X_{5:6} - 3X_{4:6} + 3X_{3:6} - X_{2:6}] = \frac{15}{2}(-14\beta_5 + 35\beta_4 - 30\beta_3 + 10\beta_2 - \beta_1).$$

The alternative expressions for the first four TL-moments when t = 1 are

$$\lambda_1^{(1)} = 6\int_0^1 Q(u)u(1-u)du, \tag{2}$$

$$\lambda_2^{(1)} = 6\int_0^1 Q(u)u(1-u)(2u-1)du, \tag{3}$$

$$\lambda_3^{(1)} = \frac{20}{3}\int_0^1 Q(u)u(1-u)(5u^2 - 5u + 1)du, \tag{4}$$

$$\lambda_4^{(1)} = \frac{15}{2}\int_0^1 Q(u)u(1-u)(14u^3 - 21u^2 + 9u - 1)du. \tag{5}$$

The TL- coefficient of variation ($\tau_2^{(1)}$), TL-coefficient of skewness ($\tau_3^{(1)}$) and TL-coefficient of kurtosis($\tau_4^{(1)}$) are defined as

$$\tau_2^{(1)} = \frac{\lambda_2^{(1)}}{\lambda_1^{(1)}}, \qquad \tau_3^{(1)} = \frac{\lambda_3^{(1)}}{\lambda_2^{(1)}}, \qquad \tau_4^{(1)} = \frac{\lambda_4^{(1)}}{\lambda_2^{(1)}}.$$

The rth TL-moment $\lambda_r^{(t)}$ can be estimated from the sample by replacing $E(X_{r+t-k:r+2t})$ with its unbiased estimator

$$\hat{E}(X_{r+t-k:r+2t}) = \frac{1}{\binom{n}{r+2t}}\sum_{i=1}^{n}\binom{i-1}{r+t-k-1}\binom{n-i}{t+k}X_{i:n},$$

which can be obtained from the results established by Downton (1966) as

$$\hat{E}(X_{k+1:k+l+1}) = \frac{1}{\binom{n}{k+l+1}}\sum_{i=1}^{n}\binom{i-1}{k}\binom{n-i}{l}X_{i:n}.$$

Thus the rth sample TL-moment $l_r^{(t)}$ is defined as

$$l_r^{(t)} = r^{-1}\sum_{k=0}^{r-1}(-1)^k\binom{r-1}{k}\hat{E}(X_{r+t-k:r+2t}), \quad r = 1,2,...n-2t,$$

which on simple re-arrangement gives the alternative form

$$l_r^{(t)} = r^{-1}\sum_{i=t+1}^{n-1}\left[\frac{\sum_{k=0}^{r-1}(-1)^k\binom{r-1}{k}\binom{i-1}{r+t-1-k}\binom{n-i}{t+k}}{\binom{n}{r+2t}}\right]X_{i:n}.$$

Now we are in a position to discuss the TL-moment for each extreme value distribution.

TL-moments for Generalized Extreme Value (GEV) Distribution:

The probability density function for GEV is given by

$$f(x) = \frac{1}{\alpha}\left\{1 - k\frac{(x-\xi)}{\alpha}\right\}^{\frac{1}{k}-1}\exp\left[-\left\{1 - k\frac{(x-\xi)}{\alpha}\right\}^{\frac{1}{k}}\right],$$

where $-\infty < x \le \xi + \frac{\alpha}{k}$ for $k > 0$ and $\xi + \frac{\alpha}{k} \le x < \infty$ for $k < 0$.

Quantile function of GEV:

$$Q(u) = \xi + \alpha Q_0(u), \tag{6}$$

where

$$Q_0(u) = [1 - (-\log u)^k]/k \cdot$$

Then combining the identities (2-5) with (6), we get the first four TL-moments for GEV as a system of equations involving the parameters α, ξ and k [see, Eq. (7)- (10)]

$$\lambda_1^{(1)} = \xi + \frac{\alpha}{k}\left\{1 - \Gamma(1+k)\left(\frac{3}{2^k} - \frac{2}{3^k}\right)\right\}, \tag{7}$$

$$\lambda_2^{(1)} = 6\alpha\Gamma k\left\{\frac{1}{2(4^k)} - \frac{1}{3^k} + \frac{1}{2^{k+1}}\right\}, \tag{8}$$

$$\lambda_3^{(1)} = \frac{20\alpha\Gamma k}{3}\left\{\frac{1}{5^k} - \frac{5}{2(4^k)} + \frac{2}{3^k} - \frac{1}{2^{k+1}}\right\}, \tag{9}$$

$$\lambda_4^{(1)} = -\frac{15\alpha\Gamma k}{2}\left\{\frac{7}{5^k} - \frac{7}{3(6^k)} - \frac{15}{2(4^k)} + \frac{10}{3^{k+1}} - \frac{1}{2^{k+1}}\right\}. \tag{10}$$

In the evaluation of the of the parameters, the sample TL-moments (l_r^1 , r=1,…,4) may be used directly. So the shape parameter k can be estimated by numerically solving the highly non linear equation given by

$$\hat{\tau}_3^{(1)} = \frac{l_3^{(1)}}{l_2^{(1)}} = \frac{10}{9}\left\{\frac{\frac{1}{5^k} - \frac{5}{2(4^k)} + \frac{2}{3^k} - \frac{1}{2^{k+1}}}{\frac{1}{2(4^k)} - \frac{1}{3^k} + \frac{1}{2^{k+1}}}\right\}. \tag{11}$$

In order to solve Eq. (11) for *k* numerically, we first generate 1,000 different values for *k* in the interval $[-1, 1]$ for suitable step size and those values are used to calculate the right hand side of the Eq. (11). If we denote the approximate right-hand side by the symbol $\tau_{3\hat{k}}^{(1)}$ for a particular value of *k*, then *k* is chosen in such a way that $\left|\hat{\tau}_3^{(1)} - \tau_{3\hat{k}}^{(1)}\right|$ is minimum. The estimates of the other two parameters α and ξ are

$$\hat{\alpha} = \frac{l_2^{(1)}}{6\Gamma\hat{k}\left\{\frac{1}{2(4^{\hat{k}})} - \frac{1}{3^{\hat{k}}} + \frac{1}{2^{\hat{k}+1}}\right\}}, \tag{12}$$

$$\hat{\xi} = l_1^{(1)} - \frac{\hat{\alpha}}{\hat{k}}\left\{1 - \Gamma(1+\hat{k})\left(\frac{3}{2^{\hat{k}}} - \frac{2}{3^{\hat{k}}}\right)\right\}. \tag{13}$$

TL-moments for Generalized Pareto Distribution (GPD):

The probability density function for GPD is given by

$$f(x) = \frac{1}{\alpha}\left\{1 - k\frac{(x-\xi)}{\alpha}\right\}^{\frac{1}{k}-1},$$

where $\xi < x \le \xi + \frac{\alpha}{k}$ for $k > 0$ and $\xi \le x < \infty$ for $k \le 0$.

Quantile function of GPD:

$$Q(u) = \xi + \alpha Q_0(u), \tag{14}$$

where

$$Q_0(u) = [1 - (1-u)^k]/k.$$

The first four TL-moments of GPD can be obtained as

$$\lambda_1^{(1)} = \xi + \frac{\alpha(k+5)}{(k+3)(k+2)}, \quad (15)$$

$$\lambda_2^{(1)} = \frac{6\alpha}{(k+2)(k+3)(k+4)}, \quad (16)$$

$$\lambda_3^{(1)} = \frac{20\alpha(1-k)}{3(k+2)(k+3)(k+4)(k+5)}, \quad (17)$$

$$\lambda_4^{(1)} = -\frac{15\alpha(k-1)(k-2)}{2(k+2)(k+3)(k+4)(k+5)(k+6)}. \quad (18)$$

The estimates of the parameters of GPD are then given by

$$\hat{k} = \frac{10-45\hat{\tau}_3^{(1)}}{10+9\hat{\tau}_3^{(1)}}, \quad (19)$$

$$\hat{\alpha} = \frac{l_2^{(1)}}{6(\hat{k}+2)(\hat{k}+3)(\hat{k}+4)}, \quad (20)$$

$$\hat{\xi} = l_1^{(1)} - \frac{\hat{\alpha}(\hat{k}+5)}{(\hat{k}+2)(\hat{k}+3)}. \quad (21)$$

TL-moments for Generalized Logistic Distribution (GLD):

The probability density function for GLD is given by

$$f(x) = \frac{1}{\alpha}\left\{1-k\frac{(x-\xi)}{\alpha}\right\}^{\frac{1}{k}-1}\left[1+\left\{1-k\frac{(x-\xi)}{\alpha}\right\}^{\frac{1}{k}}\right]^{-2},$$

where $-\infty < x \le \xi + \frac{\alpha}{k}$ for $k > 0$ and $\xi + \frac{\alpha}{k} \le x < \infty$ for $k < 0$.

Quantile function of GLD:

$$Q(u) = \xi + \alpha Q_0(u), \quad (22)$$

where

$$Q_0(u) = [1-\{(1-u)/u\}^k]/k .$$

The first four TL-moments of GLD can be obtained as

$$\lambda_1^{(1)} = \xi + \frac{\alpha}{k} + \frac{\alpha\pi(1-k^2)}{\sin(\pi k)}, \quad (23)$$

$$\lambda_2^{(1)} = -\frac{k\pi\alpha(k^2-1)}{2\sin(\pi k)}, \quad (24)$$

$$\lambda_3^{(1)} = \frac{5\alpha k^2\pi(k^2-1)}{18\sin(\pi k)}, \quad (25)$$

$$\lambda_4^{(1)} = -\frac{k\alpha\pi(7k^2+2)(k^2-1)}{48\sin(\pi k)}. \quad (26)$$

The estimates of the parameters of GLD are then given by

$$\hat{k} = \frac{-9\hat{\tau}_3^{(1)}}{5}, \quad (27)$$

$$\hat{\alpha} = -\frac{2l_2^{(1)}\sin(\pi\hat{k})}{\pi\hat{k}(\hat{k}^2-1)}, \quad (28)$$

$$\hat{\xi} = l_1^{(1)} + \frac{\pi\alpha(\hat{k}^2-1)}{\sin(\pi\hat{k})} - \frac{\hat{\alpha}}{\hat{k}}. \quad (29)$$

Table 2.1: Estimates of the parameters for each distribution using TLMOM

Stations	GPD	GLD	GEV
	TLMOM k α ξ	TLMOM k α ξ	TLMOM k α ξ
Cherrapunji	1.1292 481.5270 347.9184	.0422 87.0861 578.7018	.3640 148.7292 527.7665
Guwahati	0.1347 39.5679 69.2916	-0.3371 15.9406 96.0311	-0.2080 20.9987 87.8636
Imphal	0.2687 42.3582 49.3517	-0.2776 15.2748 76.6281	-0.1240 20.9126 68.6291
Mohanbari	0.1736 50.8200 88.3780	-0.3195 19.8242 122.2421	-0.1840 26.3986 112.0166
North Lakhimpur	0.6573 82.6589 98.3453	-0.1211 21.7072 144.7556	0.1040 32.9802 132.7214
Pacighat	0.2279 101.7598 135.9225	-0.2954 37.9533 202.4182	-0.1480 51.4108 182.6806
Silchar	0.5094 103.0872 82.6982	-0.1781 30.5187 143.6417	0.0200 44.6292 127.0704
Shillong	1.0408 156.0909 65.3129	0.0135 30.2382 142.3157	0.3160 50.5570 124.7798
Tezpur	0.6971 67.1482 63.1276	-0.1063 17.0787 100.3157	0.1280 26.2371 90.8045

2.2 Goodness of Fit (GOF)

The next step in our analysis is to evaluate the performance of the distributions. The tests applied for judging the goodness of fit for the fitted distributions for extreme rainfall data are relative root mean squared error (RRMSE), relative mean absolute error (RMAE) and probability plot correlation coefficient (PPCC). While the first two tests involve the assessment on the difference between the observed values and expected values of the assumed distributions, the last one measures the correlation between the ordered values and the corresponding expected values. The formulae for the tests are

$$\text{RRMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_{i:n}-\hat{Q}(F_i)}{X_{i:n}}\right)^2},$$

$$\text{RMAE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_{i:n}-\hat{Q}(F_i)}{X_{i:n}}\right|,$$

$$\text{PPCC}=\frac{\sum_{i=1}^{n}(X_{i:n}-\overline{X})\{\hat{Q}(F_i)-\overline{Q}(F)\}}{\sqrt{\sum_{i=1}^{b}(X_{i:n}-\overline{X})^2}\sqrt{\sum_{i=1}^{n}\{\hat{Q}(F_i)-\overline{Q}(F)\}^2}},$$

where $X_{i:n}$ is the observed values of the ith order statistics of a random sample of size n, $\hat{Q}(F_i)$ is the estimated quantile values associated with the i^th^ Gringorten plotting position, $F_i=\frac{i-.44}{n+.12}$ and $\overline{Q}(F)=\frac{1}{n}\sum_{i=1}^{n}\hat{Q}(F_i)$.

The smallest values of RRMSE and RMAE correspond to the best fitting distribution where as in the case of PPCC, the distribution with the computed PPCC closest to 1 indicates the best.

3. Results and Discussion

Extreme rainfall may result in landslides, flash floods and crop damage that have major impacts on society, the economy and the environment. Although prediction of such extreme weather events is still fraught with uncertainties, a proper assessment of likely future trends would help in setting up infrastructure for disaster preparedness. This study is intended to model maximum rainfall in the North East India. North East India is one of the major disaster prone region of India because of their unique geographical locations and physical features, witnessing the fury of monsoon. Some recent examples of such flash floods originating from extreme rainfall are two events that occurred in the north bank of the Brahmaputra river and caused significant damage to human life and property. The first of the two events occurred during the monsoon season on June 14th, 2008, due to heavy rainfall on the hills of Arunachal Pradesh north of Lakhimpur District causing flash floods in the rivers of Ranganadi, Singara, Dikrong and Kakoi that killed at least 20 people and inundated more than 50 villages leading to displacement of more than 10,000 people. The other that occurred in the post monsoon season on October 26 affected a long strip of area of northern Assam valley adjoining foothills of Bhutan and Arunachal Pradesh causing flash flooding in four major rivers (all are tributaries of the river Brahmaputra) and a number of smaller rivers. With this in mine this study is being carried to examine what kind of distribution would be appropriate for extreme rainfall. If the best fitting distribution is known for a particular station, one would be able to predict the return value of this extreme rainfall event at a specific time in the future. In this article, an attempt has been made to determine the best fitting distribution to describe the annual series of maximum daily rainfall data for the period 1966 to 2007 of nine distantly located stations in North East India. For this purpose, three extreme value distributions viz. generalized extreme value distribution (GEV), generalized logistic distribution (GLD), and generalized Pareto distribution (GPD) are used.

Table 3.1: Three goodness of fit test result for each station considered in this study

STATIONS	RRMSE			RASE			PPCC		
	GPD	GLD	GEV	GPD	GLD	GEV	GPD	GLD	GEV
Cherrapunji	0.3019	0.1045	0.0494	0.1139	0.0434	0.0058	0.9426	0.9915	0.9817
Guwahati	0.0493	0.0377	0.0105	0.0355	0.0313	0.0026	0.9738	0.9924	0.9903
Imphal	0.0756	0.0531	0.0135	0.0460	0.0285	0.0026	0.9872	0.9740	0.9832
Mohanbari	0.1337	0.1108	0.0337	0.0861	0.0673	0.0059	0.8430	0.9247	0.9046
North. Lakhimpur	0.0591	0.0339	0.0084	0.0369	0.0279	0.0021	0.9735	0.9934	0.9920
Pacighat	0.1004	0.0501	0.0177	0.0599	0.0345	0.0033	0.9464	0.9894	0.9806
Silchar	0.0647	0.0819	0.0195	0.0455	0.0587	0.0044	0.9541	0.9781	0.9738
Shillong	0.0703	0.1542	0.0282	0.0508	0.0700	0.0048	0.9634	0.9768	0.9779
Tezpur	0.0321	0.0782	0.0168	0.0198	0.0403	0.0026	0.9844	0.9856	0.9894

The first step in our analysis involves the estimation of parameters for each of the aforesaid distribution using the method of TL-moment. The parameters for the GEV, GLD and GPD distributions are estimated for each station using the methodology as stated in section 2.1 and the estimated values of the parameters are given in Table 2.1.

The next step in our analysis involves the selection of the best fitting distribution out of the three candidate distributions. It is important to note from the earlier studies (cf. Zalina *et al*. 2002; Zin *et al*. 2008; Kysely and Picek 2007) on the statistical modeling of extreme rainfall that the best fitting probability distribution may vary according to the geographical locations of the area considered and the method used to estimate the parameters. Although theoretical results (cf. Coles 2007) suggest that, for block maxima, the appropriate class is generalized extreme value distribution. The performances of the distributions are assessed with the help of three goodness of fit test which are mentioned in the section 3.2. The results of all GOF tests are given in the Table 3.1. From the results in Table 3.1, it is seen that the minimum RRMSE and RASE appears at GEV distribution in all stations considered for this study. Therefore, GEV is superior to the other two distributions under RRMSE and RASE test. This finding not only agrees with the theoretical results on modeling of block maxima values, but also supports earlier works of Zalina *et al*. (2002). But in the PPCC test the results varies from site to site. In this test the value of PPCC closest to one appears at GEV distribution for stations Shillong and Tezpur. In remaining stations, except Imphal, this value appears at GLD distribution. Under this test, we may conclude that GLD is best fitting distribution to the extreme rainfall event in North East India. Similar conclusion may be found in Zin *et al*. (2008), Kysely and Picek (2007) and Deka *et al*. (2011).

We summarize the results based on the three goodness of fit tests to decide the best fitting distribution for a particular station in Table 3.2. From the Table 3.2, it is observed that GEV is found to be the best among other fitting distributions under RRMSE and RMAE tests, but perform poorly in PPCC.

Table 3.2: Best fitting distributions according to GOF

STATIONS	RRMSE	RASE	PPCC
Cherrapunji	GEV	GEV	GLD
Guwahati	GEV	GEV	GLD
Imphal	GEV	GEV	GPD
Mohanbari	GEV	GEV	GLD
North Lakhimpur	GEV	GEV	GLD
Pacighat	GEV	GEV	GLD
Silchar	GEV	GEV	GLD
Shillong	GEV	GEV	GEV
Tezpur	GEV	GEV	GEV

From the above discussion, we can conclude that GEV is the best fitting distribution followed by GLD and GPD to describe the annual maximum rainfall data over the stations considered for this study.

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