COMPARISON OF L-MOMENTS OF EXTREME VALUE FAMILY OF PROBABILITY DISTRIBUTIONS FOR DETERMINATION OF DESIGN RAINFALL DEPTH

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ABSTRACT

Accurate estimation of extreme (i.e., 1-day maximum) rainfall is essential for water resources management, flood forecasting, agricultural planning, and climate change impact studies. This can be achieved through fitting the extreme value family of probability distributions (EVD) that consists of Extreme Value Type-1 (EV1), Extreme Value Type-2 (EV2), Generalized Extreme Value (GEV), and Generalized Pareto (GPA) to the series of observed annual 1-day maximum rainfall (AMR), whereas the parameters are determined by the Method of L-Moments (LMO). This paper presents a study on the comparison of LMO estimators of EVD for the determination of design rainfall depth at Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda rain gauge sites. For this purpose, the AMR series was generated from the daily rainfall data observed at the sites during the period 1960 to 2022 and used. The adequacy of fitting LMO of EVD to the AMR series was examined through Goodness-of-Fit (GoF) tests, viz., Chi-Square and Kolmogorov-Smirnov (KS), while the selection of the best-fit distribution was made through model performance analysis with various indicators, viz., correlation coefficient (CC), Nash-Sutcliffe model efficiency (NSE), root mean squared error (RMSE), and cross-correlation matrix analysis (CCMA). The Chi-Square test results uniformly supported the use of EV1 and GEV for modelling the AMR data of six sites, whereas KS test results supported all four distributions of EVD for all six sites. The results indicated that the CC values obtained from four distributions vary between 0.960 and 0.994. The study showed that the NSE computed by EV1, GEV, and GPA varies from 91.7% to 98.7%. The outcomes of CCMA showed that there is a perfect correlation between the estimated rainfall by EV1 and GEV, and also nearer to 1.000. On the basis of evaluation of the results with quantitative (viz., CC, NSE, and RMSE) and qualitative assessments, it was found that GEV is the best choice for rainfall estimation for Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda. The estimated extreme rainfall by GEV distribution could be considered as a design rainfall depth while planning water resources management projects and their related activities in the respective sites.

Keywords: Chi-Square, Extreme Value Type-1, Generalized Extreme Value, Kolmogorov-Smirnov, Method of L-Moments, Rainfall.

INTRODUCTION

Determination of design rainfall depth is of utmost importance in the hydraulic modelling of urban drainage systems, as it directly contributes to runoff. Analysis of rainfall characteristics is also considered as one of the effective techniques for planning water resources projects. Apart from this, design rainfall depth is needed for estimating the water requirement in a particular region. For this purpose, the Extreme Value Type-1 (EV1), Extreme Value Type-2 (EV2), Generalized Extreme Value (GEV), and Generalized Pareto (GPA), which belong to the

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13 CLIMATE ACTION

extreme value family of probability distributions (EVD), are widely applied for rainfall estimation (Prabhu et al., 2016; Seckin et al., 2011). The parameters of the distributions are generally determined by the method of moments (MoM) and maximum likelihood method (MLM). Research reports indicated that MoM is a natural and relatively easy method for determination of parameters of the distribution (Raynal & Salas, 1986). MLM is considered the most efficient method since it provides the smallest sampling variance of the computed estimators. But the MLM has the disadvantage of frequently giving biased estimates and often fails to give the desired accuracy in estimating the extremes from hydrological data (Bhat et al., 2019). To address these shortcomings, the application of an alternative approach, namely, the L-Moments (LMO), was applied for the determination of the parameters of EVD (Yue & Wang, 2004).

1. Literature Review

A number of studies on the estimation of extreme events such as rainfall, peak flood, wind speed, etc., have been carried out by different researchers using LMO of probability distributions. AlHassoun (2011) carried out a study on developing empirical formulas to estimate the rainfall intensity in the Riyadh region using EV1 (commonly known as Gumbel), LN2, and Log Pearson Type-3 (LP3). He concluded that the LP3 gives better accuracy amongst the three distributions studied in the estimation of rainfall intensity. Esteves (2013) applied the Gumbel distribution to estimate the extreme rainfall depths at different rain-gauge stations in the southeast United Kingdom. Vivekanandan (2014) applied the Gumbel distribution for modelling the seasonal and annual rainfall for the Krishna and the Godavari river basins. Rasel and Hossain (2015) applied the Gumbel distribution for the development of intensity-duration-frequency curves for seven divisions in Bangladesh. Afungang and Bateira (2016) applied the Gumbel distribution to estimate the maximum amount of rainfall for different periods in the Bamenda mountain region, Cameroon.

Studies carried out by Sasireka et al. (2019) indicated that the extreme rainfall for various return periods obtained from Gumbel distribution could be used for design purposes by considering the risk involved in the operation and management of hydraulic structures in the Tiruchirappalli region. Vivekanandan and Srishailam (2021) applied EV1, LN2, and LP3 distributions for estimation of rainfall at Anakapalli, Atchutapuram, Kasimkota, and Parvada sites. They also found that the LP3 is a better-suited probability distribution for rainfall estimation of Anakapalli, while LN2 for Kasimkota and EV1 for Atchutapuram and Parvada. Van der Spuy and Du Plessis (2022) reviewed the application of LN2, LP3, and GEV distributions in flood frequency analysis for South Africa and stated that the GEV is a preferred choice at the lower probabilities. Chen et al. (2023) made an attempt to estimate the rainfall for different return periods in the Shaoguan area through regional LMO analysis using the 24-hour annual maximum precipitation from observational rainfall and integrated multi-satellite retrievals for global precipitation mission gridded rainfall. Shah and Pan (2024) applied EV1, GEV, LN2, LP3, Gamma, and Normal distributions for FFA of Ram Munshibagh and Asham gauge sites in the Jhelum basin of the North-Western Himalayas, India. Diop et al. (2025) carried out FFA in West Africa using LMO, MLE (Maximum Likelihood Estimation), and GMLE (Generalized MLE) methods of GEV and EV1 (also known as Gumbel) probability distributions. The adequacy of fitting LMO of EVD to the AMR series was examined through Goodness-of-Fit (GoF) tests, viz., Chi-Square and Kolmogorov-Smirnov (KS), while the selection of the best-fit method of EV1 was made through model performance analysis (MPA) with various indicators, viz., correlation coefficient (CC), Nash-Sutcliffe model efficiency (NSE), root mean squared error (RMSE), and cross-correlation matrix analysis (CCMA). This paper presents the methodology adopted in rainfall estimation using LMO estimators of EVD with an illustrative example and the results obtained therefrom.

2. Methodology

The steps involved in the determination of design rainfall depth include (i) computing the parameters of EVD using LMO and estimating rainfall for different return periods; (ii) evaluating the adequacy of fitting EVD to the AMR series using quantitative (viz., GoF tests, MPA, and CCMA) and qualitative (viz., fitted curves of the estimated rainfall) assessments; and (iii) analyzing the results and making discussions thereon.

2.1 Theoretical Description of LMO

LMOs are analogous to ordinary moments, which provide measures of location, dispersion, skewness, kurtosis, and other aspects of the shape of the distributions or data samples. Let x(1), x(2), ..., x(N) be a conceptual random sample of size N and x(1N)<x(2N)<.....<x(NN) denote the corresponding order statistics. The r+1th LMO is defined by Hosking and Wallis (1993) and is given by Equation 1.

$$\lambda(r+1)=\sum_{k=0}^{r}\frac{(-1)^{r-k}(r+k)!}{(k!)^2(r-k)!}b(k) \quad (1)$$

where, λ(r+1) is the r+1th sample moment and Equation 2. b(k) is an unbiased estimator with

$$b(k)=\frac{1}{N}\sum_{i=k+1}^{N}\frac{(i-1)(i-2).....(i-k)}{(N-1)(N-2).....(N-k)}x(iN) \quad (2)$$

Table 1 presents the CDF of EVD, extreme rainfall [x(T)] for a given return period (T), and LMO estimators of EVD. In Table 1, F(x) is the Cumulative Distribution Function (CDF) of a random variable x [i.e., Annual 1-day Maximum Rainfall (AMR)], ξ is the location parameter, α is the scale parameter, k is the shape parameter, x(i) is the observed AMR of the ith sample, λ(1) and λ(2) are the first and second LMOs, and N is the sample size.

2.2 Goodness-of-Fit Tests

Out of a number of GoF tests available, the most widely accepted tests in rainfall frequency analysis are Chi-Square and KS, which are used in the study. The theoretical descriptions of GoF test statistics (Zhang, 2002).

χ^2 test statistic is defined by Equation 3:

$$\chi_C^2=\sum_{j=1}^{NC}\frac{\left(O_j(x)-E_j(x)\right)^2}{E_j(x)} \quad (3)$$

where $O_j(x)$ is the observed frequency value (x) of the jth class, $E_j(x)$ is the expected frequency value (x) of the jth class and NC is the number of frequency classes. The rejection region of χ^2 statistic at the desired significance level (η) is given by $\chi_C^2 \geq \chi^2_{1-\eta,NC-m-1}$. Here, m denotes the number of parameters of the distribution and χ^2_C is the computed value of χ^2 statistic by the distribution.

KS test statistic is defined by Equation 4.

$$KS=\underset{i=1}{\overset{N}{Max}}[F_e(x(i)-F_c(x(i)] \quad (4)$$

where F_e[x(I)] = m/(N+1) is the empirical CDF of x(i), F_c [x(i)] is the computed CDF of x(i) of the ith sample by EVD, and m is the rank assigned to the random variables [x(i), i = 1 to N] that are arranged in ascending order. If the computed values of the GoF test statistic given by the distribution are not greater than its theoretical values at the desired level of significance, then the distribution is considered to be adequate for rainfall estimation at that level.

2.3 Model Performance Analysis

The theoretical descriptions of model performance indicators (viz., CC, NSE, and RMSE) (Vivekanandan and SriShailam., 2021) applied in selecting the best fit distribution for rainfall estimation are given by Equations 5-7.

$$CC=\frac{\sum_{i=1}^{N}[x(i)-\mu(x)][(y(i)-\mu(y)]}{\sqrt{\left(\sum_{i=1}^{N}[x(i)-\mu(x)]^2\right)\left(\sum_{i=1}^{N}[(y(i)-\mu(y)]^2\right)}} \quad (5)$$

EVD	CDF [F(x)]	x(T)	LMO Estimators
OEV1 (ξ, α)	$F(x)=\exp\left(-\exp-\left(\frac{x-\xi}{\alpha}\right)\right),\alpha>0$	$x(T)=\xi-\alpha\ln\left[-\ln(1-(1/T))\right]$	ξ = λ (1) - (0.5772157) α and λ (2)= α (ln2) $\lambda(1)=b(0)=\frac{1}{N}\sum_{i=1}^{N}x(i);\ b(1)=\frac{1}{N(N-1)}\sum_{i=2}^{N}(i-1)[x(i)]$
Ev2 (α, k)	$F(x)=\exp\left(-\left(\frac{x}{\alpha}\right)^{-k}\right),\alpha>0,k>0$	$x(T)=\alpha\ \left[-\ln\left(1-(1/T)\right)\right]^{-(1/k)}$	By using logarithmic transformation of the observed data, the parameters of EV1 are initially obtained by LMO. These parameters are used to determine the parameters of EV2 from α = e^{ξ} and k=1/(scale parameter of Ev1).
GEV (ξ, α, k)	$F(x)=\exp\left(-\left[1-\frac{k(x-\xi)}{\alpha}\right]^{1/k}\right),\alpha>0$	$x(T)=\xi+\frac{\alpha}{k}\left(1-\left[-\ln(1-(1/T))\right]^{k}\right)$	z = [2/((3 + t_3) - (ln 2/ln 3))]; t_3 = (2 (1 - 3^{-k})/(1 - 2^{-k}))-3 k = 7.8590z + 2.9554z^2; α = λ(2) k/[(1 -2^{-k})Γ(1 + k)]; ξ = λ(1) + [α(Γ(1 + k) - 1)/k]
GPA (ξ, α, k)	$F(x)=1-\left[1-\frac{k(x-\xi)}{\alpha}\right]^{\frac{1}{k}},\alpha>0,k>0$	$x(T)=\xi+\frac{\alpha\left[1-(1/T)^{k}\right]}{k}$	ξ = λ(1) + λ(2)[k + 2]; t_3 = (1 - k)/(3 + k); k = [4/t_3 + 1)] - 3; α = (1 + k)(2 + k) λ(2)

Table 1. CDF, Extreme Rainfall and LMO Estimators of EVD (Rao & Hamed 2019)

$$NSE\,(\%) = \left(1 - \frac{\sum_{i=1}^{N} [x(i) - y(i)]^2}{\sum_{i=1}^{N} [x(i) - \mu(x)]^2} \right) * 100 \quad (6)$$

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^{N} [(x(i) - y(i)]^2 \right)^{1/2} \quad (7)$$

Where x(i) is the observed AMR of the i^{th} sample, y(i) is the estimated AMR of the ith sample, mu(x) is the average of the observed AMR, and mu(y) is the average of the estimated AMR. The parameter estimation method with high CC, better NSE, and minimum RMSE is considered as better suited for rainfall estimation.

3. Study Area and Data Used

In this paper, a study on the comparison of LMO estimators of EVD for the determination of design rainfall depth at six rain gauge sites (RGS) located in the surrounding regions of the Tapi River was carried out. The Tapi River basin extends over the states of Madhya Pradesh, Maharashtra, and Gujarat, having a total catchment area of about 65,145 km². It lies between longitudes 72° 33' to 78° 17' E and latitudes 20° 9' to 21° 50' N. For the present study, the AMR series was extracted from the daily rainfall data observed at Akkalkuwa, Kamraj, Navapur, Sakari, Shahada, and Taloda RGS during the period 1960 to 2022 and used for rainfall estimation by employing LMO estimators of EVD (viz., EV1, EV2, GEV, and GPA). Figure 1 shows the index map of the study area with locations of six RGS, whereas the descriptive statistics of the AMR series are given in Table 2.

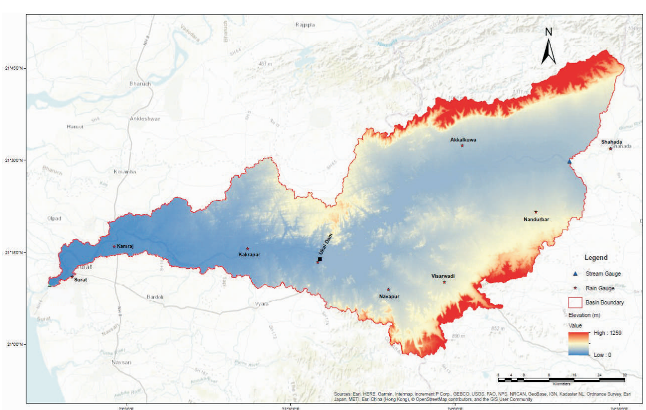

Figure 1. Index Map of the Study Area with Locations of Six RGS

RGS	Descriptive statistics of AMR				
	Average (mm)	SD (mm)	CV (%)	C_s	C_k
Akkalkuwa	119.4	53.9	45.1	0.649	-0.675
Kamrej	172.5	74.7	43.3	1.110	1.823
Navapur	137.3	70.2	51.1	1.455	1.621
Sakri	73.7	28.7	39.0	1.827	4.898
Shahada	82.6	33.6	40.7	0.744	0.292
Taloda	93.0	43.2	46.5	1.672	4.044

SD: Standard Deviation; C_s: Coefficient of skewness; C_k: Coefficient of kurtosis

Table 2. Descriptive Statistics of the AMR Series of Six RGS

It is noted that the average and SD of AMR data pertaining to Kamrej are higher than those values of the other five sites considered in the study. The coefficient of variation (CV) [i.e., (Average/SD)*100] of AMR of six sites varies between 39.0% and 51.1%. Also, from Table 2, it can be found that the higher-order moments (Cs and Ck) of six sites have different behaviors from each other.

4. Results and Discussion

By applying the procedures of EVD, as described above, the rainfall estimation at six RGS was carried out, and the results are presented in the ensuing sections.

4.1 Estimation of Extreme Rainfall by EVD

The AMR series of six RGS was applied in determining the LMO estimators of EVD and used for estimation of extreme (i.e., annual 1-day maximum) rainfall, and the results are presented in Table 3. From the results, it is noted that the estimated rainfall by EV2 for a return period from 2 years to 100 years is higher than those values of EV1, GEV, and GPA for all six sites. From Table 3, it is also noted that the variations between the estimated rainfall by EV1 and GEV for a return period from 2 years to 100 years are minimal. From Figure 2 (a-f), it can be seen that the fitted curves using EV2 and GPA are not in the form of linear curves, and the estimated rainfall using GPA is less than those values of EV1, EV2, and GEV for Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda.

4.2 Analysis of Results Based on GoF Tests

The adequacy of fitting LMO estimators of EVD to the AMR series of six sites was evaluated through GoF tests, and the results are presented in Table 4. From Chi-Square test results, it is noted that the computed values by LMO

RGS	EVD	1-Day Maximum Rainfall (mm) for Different Return Periods (in Year)							
		2	5	10	20	25	50	75	100
Akkalkuwa	EV1	110.2	159.8	192.7	224.3	234.3	265.1	283.0	295.7
	EV2	100.2	145.2	185.6	234.8	253.1	318.5	364.1	400.2
	GEV	109.6	159.2	192.7	225.2	235.7	268.0	287.0	300.6
	GPA	108.0	167.3	200.2	225.4	232.1	249.8	258.2	263.4
Kamrej	EV1	160.0	227.0	271.3	313.7	327.2	368.7	392.9	410.0
	EV2	147.4	208.8	262.9	327.9	351.8	436.6	495.0	541.0
	GEV	159.2	226.1	271.2	315.2	329.2	373.0	398.7	417.0
	GPA	157.0	236.9	281.3	315.4	324.6	348.6	359.9	367.0
Navapur	EV1	126.2	185.9	225.5	263.5	275.6	312.7	334.2	349.5
	EV2	113.7	167.3	216.1	276.2	298.5	379.3	436.0	481.2
	GEV	118.1	175.6	222.1	274.5	292.8	355.5	396.5	427.8
	GPA	115.7	183.6	233.3	281.7	297.0	343.7	370.5	389.2
Sakri	EV1	69.3	93.1	108.9	124.0	128.8	143.6	152.2	158.3
	EV2	65.4	87.9	106.9	128.9	136.8	164.2	182.7	197.0
	GEV	67.7	91.3	108.6	126.5	132.5	151.9	163.9	172.6
	GPA	66.8	94.9	112.7	127.9	132.3	144.6	151.0	155.2
Shahada	EV1	76.8	107.7	128.2	147.8	154.1	173.3	184.4	192.3
	EV2	71.2	99.7	124.6	154.4	165.2	203.7	230.0	250.7
	GEV	77.6	108.4	128.2	146.6	152.3	169.8	179.7	186.6
	GPA	76.7	113.6	132.3	145.7	149.1	157.6	161.5	163.7
Taloda	EV1	86.2	122.7	146.9	170.1	177.4	200.1	213.3	222.6
	EV2	79.2	112.7	142.2	177.8	190.9	237.5	269.7	295.0
	GEV	83.6	119.7	146.4	174.1	183.4	213.5	232.1	245.9
	GPA	82.2	125.3	152.7	176.3	183.2	202.6	212.6	219.3

Table 3. Estimated 1-Day Maximum Rainfall for Different Return Periods by LMO of EVD

estimators of EV1 and GEV are not greater than their theoretical values at a 5% significance level (viz., 11.1 for GEV and GPA, whereas 12.6 for EV1 and EV2), and at this level, both EV1 and GEV are uniformly acceptable for modelling the AMR data of Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda. From Table 4, it is also noted that the computed values of the KS test statistic by LMO estimators of EVD are less than its theoretical value of 0.171 at a 5% significance level, and at this level, all four distributions belong to EVD for acceptable modelling of the AMR data of Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda.

4.3 Model Performance Analysis

The model performance indicators, viz., CC, NSE, and RMSE, were computed by LMO estimators of EVD and are presented in Table 5. These indicators were further used in selecting the best-fit distribution for rainfall estimation at six sites. For all six sites, it can be found that the model efficiency (NSE) obtained from EV1, GEV, and GPA varies from 91.7 to 98.7%. Likewise, the CC computed by EV1, GEV, and GPA varies between 0.960 and 0.994. From Table 5, it is noted that the RMSE computed by LMO estimators of GEV are at a minimum for Kamrej, Sakri, Shahada, and Taloda, whereas GPA provides minimum RMSE for Akkalkuwa and Navapur. However, the selection of the best-fit distribution was made through qualitative assessment using the fitted curves of the estimated rainfall together with the computed values of RMSE by EVD.

4.4 Cross Correlation Matrix Analysis

The Cross Correlation Matrix Analysis (CCMA) was made to examine the correlation between the observed and estimated values using LMO estimators of EVD, and the results are given in Table 6. The outcomes of CCMA showed that there is a perfect correlation between the estimated rainfall by EV1 and GEV, and also nearer to 1.000.

4.5 Selection of Best Fit Distribution for Rainfall Estimation

The selection of the best fit among four distributions belonging to EVD was made through the outcomes of MPA, CCMA, and fitted curves of the estimated rainfall. Qualitative assessment of the fitted curves showed that the GPA is not giving any satisfactory results in the upper

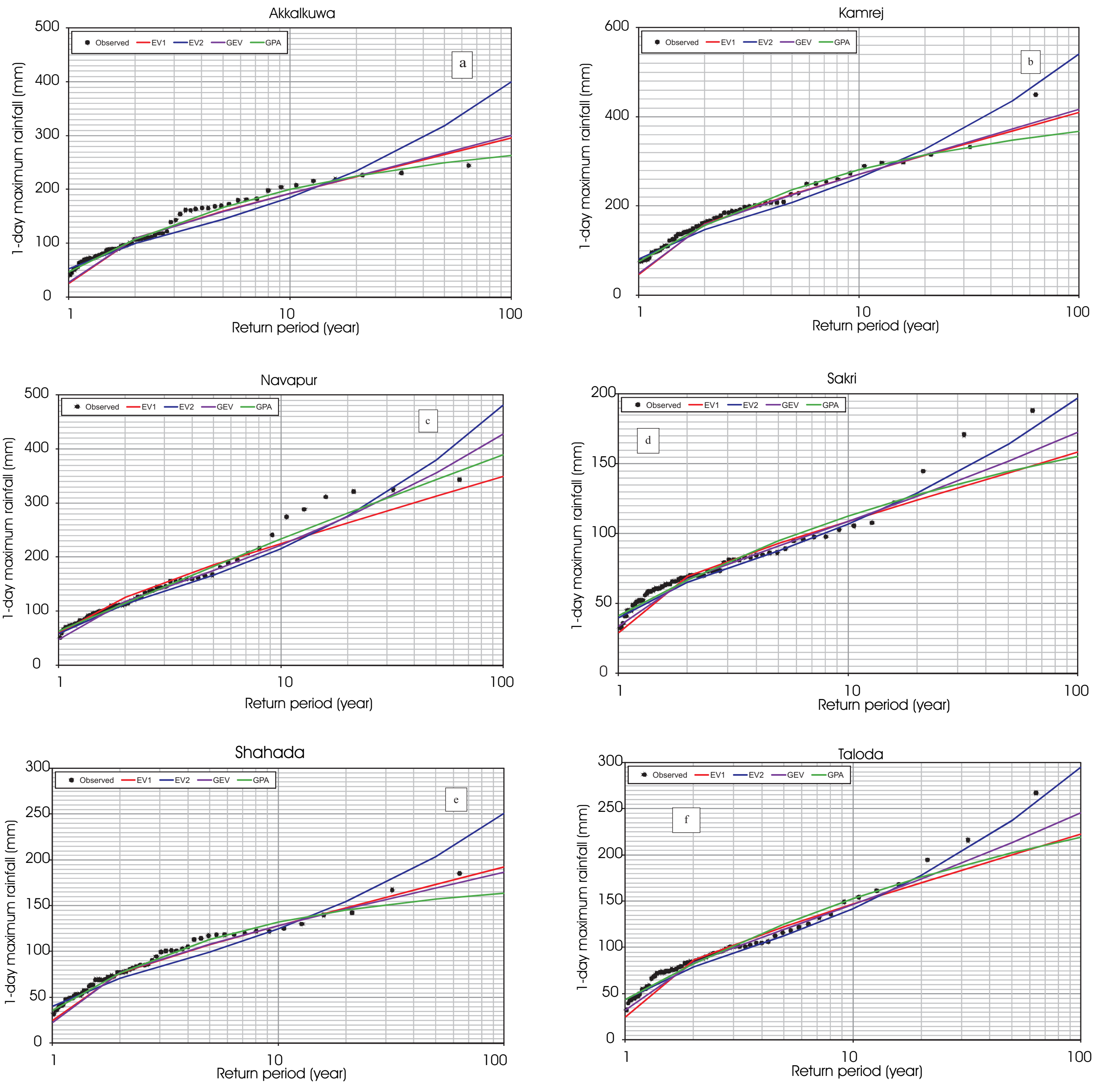

Figure 2. (a-f): Estimated 1-day maximum rainfall by LMO of EVD and observed AMR data of Six RGS of river Tapi

tail region for Akkalkuwa and Navapur, though the RMSE computed by the GPA is lower than those values of EV1, EV2, and GEV. By eliminating the GPA from the pool of EVD, it is noted that the RMSE of GEV is the second minimum next to GPA and hence identified as the best fit distribution for rainfall estimation for Akkalkuwa and Navapur. Likewise, the GEV is found to be suitable for rainfall estimation of Kamrej, Sakri, Shahada, and Taloda because the RMSE of GEV is minimum compared to those values of EV1, EV2, and GPA.

Conclusion

This paper presented a study on the comparison of LMO estimators of EVD for the determination of design rainfall at Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and

RGS	χ^2				KS			
	EV1	EV2	GEV	GPA	EV1	EV2	GEV	GPA
Akkalkuwa	9.143	14.571	11.014	9.429	0.104	0.149	0.107	0.075
Kamrej	3.143	14.857	3.429	1.429	0.062	0.125	0.062	0.067
Navapur	8.286	5.429	5.714	2.000	0.091	0.068	0.043	0.170
Sakri	5.429	5.714	7.143	13.143	0.077	0.089	0.061	0.158
Shahada	5.143	15.714	4.286	3.143	0.066	0.125	0.063	0.066
Taloda	7.714	14.286	4.857	12.286	0.078	0.109	0.073	0.215

Table 4. Computed Values of GoF Tests Statistic by LMO of EVD for Six RGS

RGS	EV1	EV2	GEV	GPA
Akkalkuwa				
CC	0.984	0.929	0.983	0.994
NSE (%)	96.7	85.3	96.5	98.7
RMSE (mm)	10.0	20.5	9.7	6.1
Kamrej				
CC	0.992	0.977	0.993	0.984
NSE (%)	98.0	95.0	98.2	96.8
RMSE (mm)	10.4	16.6	9.9	13.2
Navapur				
CC	0.974	0.972	0.983	0.989
NSE (%)	94.2	93.8	96.0	97.4
RMSE (mm)	16.8	17.3	13.9	11.1
Sakri				
CC	0.969	0.989	0.981	0.960
NSE (%)	92.8	96.5	95.1	91.7
RMSE (mm)	7.6	6.5	6.3	8.2
Shahada				
CC	0.994	0.960	0.994	0.990
NSE (%)	98.6	91.5	98.6	98.0
RMSE (mm)	4.0	9.7	3.9	4.7
Taloda				
CC	0.979	0.994	0.991	0.975
NSE (%)	94.9	97.7	97.2	94.6
RMSE (mm)	9.7	7.4	7.2	10.0

Table 5. MPIs Computed by LMO of EVD for Six RGS

Taloda RGS, located in the surrounding regions of the Tapi River. The selection of the best fit amongst four distributions of EVD applied in rainfall estimation was made through GoF (viz., Chi-Square and Kolmogorov-Smirnov) tests, model performance analysis (MPA) using various indicators (viz., CC, NSE, and RMSE), and cross-correlation matrix analysis (CCMA). On the basis of evaluation of the results through quantitative and qualitative assessments, some of the conclusions drawn from the study are presented as given below:

- Chi-Square test results uniformly supported the use of EV1 and GEV for modelling the AMR data of all six RGS, whereas KS test results supported the use of EV1, EV2, GEV, and GPA for all six RGS.

RGS	OBS	EV1	EV2	GEV	GPA
Akkalkuwa					
OBS	1.000				
EV1	0.984	1.000			
EV2	0.929	0.965	1.000		
GEV	0.983	1.000	0.968	1.000	
GPA	0.994	0.994	0.947	0.993	1.000
Kamrej					
OBS	1.000				
EV1	0.992	1.000			
EV2	0.977	0.969	1.000		
GEV	0.993	1.000	0.972	1.000	
GPA	0.984	0.994	0.953	0.993	1.000
Navapur					
OBS	1.000				
EV1	0.974	1.000			
EV2	0.972	0.962	1.000		
GEV	0.983	0.985	0.995	1.000	
GPA	0.989	0.986	0.986	0.996	1.000
Sakri					
OBS	1.000				
EV1	0.969	1.000			
EV2	0.989	0.978	1.000		
GEV	0.981	0.996	0.992	1.000	
GPA	0.960	0.994	0.981	0.994	1.000
Shahada					
OBS	1.000				
EV1	0.994	1.000			
EV2	0.960	0.971	1.000		
GEV	0.994	1.000	0.964	1.000	
GPA	0.990	0.991	0.941	0.992	1.000
Taloda					
OBS	1.000				
EV1	0.979	1.000			
EV2	0.994	0.968	1.000		
GEV	0.991	0.996	0.987	1.000	
GPA	0.975	0.994	0.973	0.995	1.000

Table 6. CCM Between the Observed and Estimated AMR by LMO of EVD

- Model efficiency (NSE) obtained from EV1, GEV, and GPA varies from 91.7 to 98.7%.
- The CC values computed by EV1, GEV, and GPA vary between 0.960 and 0.994.
- RMSE computed by LMO estimators of GEV are minimum compared to those values of other

distributions considered in rainfall estimation for Kamrej, Sakri, Shahada, and Taloda, whereas GPA provides minimum RMSE for Akkalkuwa and Navapur.

- On the basis of evaluation of the results through quantitative and qualitative assessments, it was found that GEV is the best choice for rainfall estimation for different return periods for Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda.

The study suggested that the estimated extreme (i.e., 1-day maximum) rainfall by GEV distribution for Akkalkuwa, Kamrej, Navapur, Sakri, Shahada, and Taloda could be considered as a design rainfall depth while planning water resources management projects and their related activities in the respective sites.

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