Effect of record length and recent past events on extreme precipitation analysis

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Risk of possible damage to important hydraulic structures needs to be kept at the minimum by suitably modelling environmental parameters like rainfall for extreme values of desired return period. Efficient estimation of such meteorological extremes depends on the historical records available at the site of interest. Each of the sampled data is essentially a signal from the natural system and in any statistical analysis uncertainty about the underlying phenomenon gets reduced with increase in the record length. In this article, the effect of record length on the extreme value estimates of daily rainfall at Colaba and Santacruz using theoretically appropriate generalized extreme value (GEV) model has been analysed. The study indicates that estimates for different return periods get stabilized with the increase in the length of record. Data analysis-based recent past records at Colaba give comparatively higher estimates which can possibly be attributed to increased variation and observance of more number of extreme events during the recent past. The heavy rainfall of 944.2 mm recorded at Santacruz on 26 July 2005 has shown an extraordinary effect on extreme value estimates. A possibility of temporal dependence in the series requires further studies by parameterization of trend in the GEV model.

Keywords: Extreme precipitation analysis, generalized extreme value model, hydraulic structures, return level, return period.

RISK analysis is essential while deciding whether a hydraulic project should be allowed to go forward in a zone of certain risk, for selection of a site or to design important civil structures to withstand meteorological extremities that are likely to occur during the lifetime of the structures. As such, estimation of extreme values of meteorological parameters such as rainfall intensity/quantum, maximum/minimum temperature, wind speed, mean sea-level pressure during cyclonic storms, etc. is an important aspect for protection of structures against natural disasters.

The meteorological parameters required to be used as the basis for design should have a very low exceedance probability of occurrence during the lifetime of the facility. This is generally achieved by carrying out extreme value analysis (EVA) of recorded meteorological data to arrive at design basis values according to the requirement. The motivation for analysing extremes is often to find an optimum balance between adopting high safety standards that are costly on the one hand, and preventing major damage to equipment and structures from extreme events that is likely to occur during the useful life of such infrastructure, on the other hand. A relation between the magnitude, design period in years and the probability of not exceeding that magnitude in the design period was derived by Riggs.

The information on extreme rainfall forms an important input to other hydrological processes that need to be critically examined for maximum water level at a proposed site due to extreme floods. Confidence levels of the statistically derived value depend on the size of the data as well as the data scatter with respect to fitted probability distribution function. For generating the design basis value of the parameter for a specified degree of risk to the structure involved, one can prescribe a mean recurrence interval (MRI) which is the mean time between the occurrences of two events that are equal or greater than a given magnitude[1]. For example, the Atomic Energy Regulatory Board (AERB) has prescribed a MRI of 1000 years for the design parameter maximum daily rainfall and of 10,000 years for extreme wind. Sea dams in the Netherlands are dimensioned for the one in 10,000 year event. It is important to remember that the uncertainty in the projected extreme events will increase as the return period approaches the length of the data available and increases still further as the return period exceeds the length of the data series[2].

The standard practice in assessing current meteorological conditions at any location is to use historic records representative of the point of interest to calculate extreme value statistics. The purpose of this article is to present the effect of length of recorded data on the estimates of extreme values and also to discuss the impact of recent events with increased variability that have been observed during the last couple of decades.

Aims and objectives

A general rule in any statistical analysis is that the uncertainty about a system gets reduced with more observa-

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tions recorded from the system. That is, with the increase in the record length, we will get closer to the true value of the population parameter, which is unknown. Thus, the size of the available historical database plays a vital role in the analysis of hydro-meteorological extremes. For a better reliability of estimates in EVA, the amount of data needed should be commensurate with the need of a MRI for which the estimates are required. Normally, for a few hundreds of years of MRI, a minimum of 30 years data should be used. For higher MRIs, database of around 100 years is ideal. However, as such extensive database is normally not available, even 50 years database, if available, can be used for 1000 years MRI[1].

Papalexiou and Koutsoyiannis[3] analysed the annual maximum daily rainfall of 15,137 records from all over the world, with lengths varying from 40 to 163 years, by fitting generalized extreme value (GEV) distribution. The analysis reveals that the record length strongly affects the estimation of GEV shape parameter and long records are needed for reliable estimates. Therefore, for assessing the effect of record length on the extreme value estimates, historical database has been divided into subgroups of different sizes and its impact on efficiency of estimates is assessed in this article. Nowadays, there is concern about global warming, related climate change and its overall impact on hydro-meteorological parameters. With climate change it is likely that there will be change in some extremes that lie outside the envelope of constant variability assumed under stationary climate conditions. It is possible to account for this 'non-stationarity', but the best way to do so is still under debate[4]. A general observation is that during the last couple of decades, there has been an increase in the variation of hydro-meteorological parameters such as temperature, rainfall, streamflow, etc. Historical data are therefore analysed by separating out the events that occurred during the recent past and their effect on extreme value estimates are studied. The projection of extreme values of environmental parameters likely to be encountered in the future using historically observed data has been carried out using statistical frequency analysis and extreme value theory (EVT), which is discussed below.

Material and methods

Extreme value theory and the GEV model

There is a long tradition of applying the statistics of extremes to weather and climate, starting at least as early as Gumbel in 1942. The objective of EVA is to model the observed data extremes and hence to allow generalization about the likely recurrence of these events. EVT can be traced back to the pioneering work of Fisher and Tippet in 1928, wherein the limits for the distributions of maxima of samples of independent and identically distributed (iid) random variables were shown to converge to one of three forms of extreme value distributions, called types I, II and III, when the number of selected extreme values is large.

Suppose one has a sample $X_1, X_2, \ldots, X_n$ of iid random variables from an unknown distribution function F. The main objective of EVT is to try to model the tail of F. Theoretically, if the distribution of daily rainfall is known or justifiably assumed, then one could argue, based on EVT, that the distribution of the annual maxima of daily rainfall would resemble one of the three limiting types: (a) type I known as Gumbel; (b) type II known as Fréchet, and (c) type III known as reversed Weibull. The three extremal distributions describe different limiting behaviours in the tail of the distribution. Moreover, the three types of distribution can be combined into one parametric family: the GEV family of distributions. The cumulative distribution function of the GEV distribution is given by:

$$F(x) = \mathrm{e}^{-(1-\gamma(x-\mu)/\sigma)^{-1/\gamma}},$$

for all x such that $1 + \gamma(x - \mu/\sigma) > 0$, where γ is a shape parameter, $\sigma > 0$ is a scale parameter and μ is a location parameter. The shape parameter controls the tail behaviour of the probability distribution. To fit the appropriate function to the tail of the distribution, one has then to decide on the shape and on the appropriate location and scaling constants.

The three parameters of the GEV distribution may be estimated from a sample data by a variety of techniques. Once the GEV parameters have been determined, the return level for a given return period, T, can be readily calculated. In the current context, the return level can be thought of as that value of daily rainfall that can be expected to be realized on an average every T years over a long period of time in a stationary climate. Alternatively, the return level is expected to occur in any single year with a probability of $1/T$. Formally, the cumulative probability of non-exceedence is given by

$$F(x_T) = P(X \le x_T) = 1 - \frac{1}{T}.$$

Solving for x_T using the definition of the GEV distribution yields:

$$x_T = \begin{cases} \mu + \dfrac{\sigma}{\gamma}\left[1 - \left\{1 - \ln\left(1 - \dfrac{1}{T}\right)\right\}^{\gamma}\right], & \gamma \ne 0, \\ \mu - \sigma \ln\left(-\ln\left(1 - \dfrac{1}{T}\right)\right), & \gamma = 0. \end{cases}$$

Basic assumptions that should be evaluated prior to performing the EVA are: the data are independent and identically distributed random events; they are from the sample population; they are assumed to be representative of the population and the process generating these events is stationary with respect to time. The validity of these four assumptions can be evaluated using well-known statistical tests.

Reliability of the return period rainfall and issues related to data

The return period T is best thought of as the inverse of a probability, e.g. the rainfall corresponding to $T = 50$ has a probability of 0.02 of being exceeded each year. Risk can also be expressed in terms of return period rainfall. The rainfall corresponding to $T = 238$ years has a probability of 0.9 of not being exceeded during the next 25 years, i.e. the risk r is 0.1 (ref. 5). Assuming that the annual maxima are statistically independent and are drawn from the same distribution

$$T = \frac{1}{1-(1-r)^{1/n}},$$

where the design horizon is n years and the risk is r.

The studies carried out by Fitzgerald *et al.*[6] on point rainfall frequencies in Ireland showed that accepting the current consensus on the high likelihood of changes in the precipitation climate, there seems to be little sense in estimating 500-year return period rainfall. In fact, the above equation indicates that estimating a 10% risk for a time horizon of 50 years requires a return period rainfall for 475 years.

For statistical reasons, a valid analysis of extremes in the tails of the distribution requires long time series to obtain reasonable estimates of intensity and frequency of rare events. As noted in IPCC[7], in many regions of the world it is not yet possible to make firm assessments of how global warming has affected extremes due to lack of high-quality daily observation records covering multiple decades. As a result, far less is known about past changes in extremes than past changes in mean climate. Even where the necessary data are available, systematic changes in extremes may be difficult to detect locally if there is a large amount of natural inter-annual variability in extremes[4].

In many daily resolution climatic time series, a number of observation days are missing. A particular concern regarding missing observation days in the case of an extreme analysis is that an extreme event might have been responsible for the failure of the observing system and thus the fact that the observation for that day is missing; such 'censoring' of extremes would result in negatively biased estimates of the intensity of rare events[4]. Similarly, extreme events are often localized and so some could be missed by the rain gauge network. Great care must be taken in determining whether identified outliers are truly erroneous because their inclusion, adjustment or exclusion can profoundly affect subsequent extremes analyses.

Usually the daily rainfall totals are measured for discrete, fixed, 24 h duration, 0830–0830 h, at ordinary rain gauge (ORG) stations, whereas automatic rain gauge (ARG) station have a facility of measuring rainfall depths on a sliding duration. Generally, rainfall depths measured on sliding duration are a more realistic measure of 1-day rainfall than that based on discrete, fixed, 24 h duration.

Study area

For critically analysing the effect of size of the sample on the estimates of extreme events, particularly on the efficiency of higher-order return-level estimates, daily rainfall recorded at Colaba (1901–2004) and Santacruz (1950–2005) meteorological stations of India Meteorological Department (IMD) has been used. Colaba meteorological station is located in the southern part of Mumbai city, while Santacruz station is located in suburban Mumbai. Mumbai Metropolitan Region falls in the west coast of India between 18°52′N and 19°10′N lat. and 72°48′E and 72°58′E long. Over 95% of monsoon rainfall occurs primarily during June–October, 70% of the average annual rainfall occurs in July and August and 50% of this occurs in just two or three events[8]. On 26 July 2005, the region received heavy rainfall totalling 944.2 mm in a period of 24 h, as recorded at the Santacruz station. The *Probable Maximum Precipitation* (*PMP*) *Atlas* for India published by the Indian Institute of Tropical Meteorology (IITM)[9] gives a PMP estimate of 700 mm for the Mumbai region, indicating that the July 2005 rainfall event was extraordinarily high that has resulted in catastrophic flooding[10]. It is therefore interesting to see the effect of such extraordinarily high events in EVA analysis.

Results and discussion

Data analysis has been carried out using software packages available in the free, open-source statistical software language and environment called R[11], as the academic recognition for R packages is increasing.

In EVA, we try to estimate T-year design value of hydro-meteorological parameters where T is usually very high, say, 100 or 1000 years based on n years available historical record. Whereas, practically the available size of the sample is usually very small, say, of the order of 30 or 50 years. Availability of enough data for carrying out EVA is a concern in hydro-meteorological studies. In fact, what is the requisite size of sample for estimating higher-order return levels with MRI 1000 or 10,000 years is unknown. Practically, once the distribution is fitted to available data, EVT allows us to compute return level for

Table 1. Testing randomness, independence and stationarity of data series on annual maximum daily rainfall using Wald–Wolfowitz run test at 5% significance level

	Station												
	Colaba											Santacruz	
Data series	1901–1920	1901–1935	1901–1950	1901–1970	1901–1990	1901–2004	1901–1935	1936–1970	1971–2004	1901–1950	1951–2000	1950–2004	1950–2005
Test statistic	–0.230	–2.399	–2.572	–0.963	–0.424	–1.182	–2.399	1.035	0.000	–2.572	1.143	–1.495	–1.888
P value	0.82	0.02	0.01	0.34	0.67	0.24	0.02	0.30	1.00	0.01	0.25	0.14	0.06

any order of MRI, but with what efficiency is the real matter of concern. As soon as the size of the sample increases, the uncertainty about the underlying system decreases and the estimates of design storms for different MRIs actually get converged to true but unknown values.

The size of the available historical data is important in estimating return levels of higher periods using the analysis of annual extreme events by statistical frequency method. This has an effect on the efficiency of the estimates of model parameters and hence on the estimated return levels. For assessing the effect of size of the sample in the analysis of annual extremes, historical data have been divided into different subgroups as given below. EVA for different return periods $T = 2$, 5, 10, 50, 100, 200, 500 and 1000 years has been carried out and the results are discussed below.

Case-1: Colaba 1901–1920 ($n = 20$), 1901–1935 ($n = 35$), 1901–1950 ($n = 50$), 1901–1970 ($n = 70$), 1901–1990 ($n = 90$) and 1901–2004 ($n = 104$).
Case-2: Colaba 1901–1935 ($n = 35$), 1936–1970 ($n = 35$) and 1971–2004 ($n = 34$).
Case-3: Colaba 1901–1950 ($n = 50$ years) and 1951–2000 ($n = 50$).
Case-4: Santacruz 1950–2004 ($n = 55$) and 1950–2005 ($n = 56$).

The statistical assumption of randomness, independence and stationarity of data series in respect of all the above cases have been tested using Wald–Wolfowitz (1943) run tests. The test results are given in Table 1. For Colaba station, it can be seen that there is evidence against randomness in series based on the first half of the 20th century, except for the 1901–1920 series where the sample size is insufficient to make any meaningful inference. For Santacruz station, although the data series 1950–2004 is random, when the extraordinary event of 2005 is included, the *P* value is reduced up to 0.06, which is just above the 5% level at which the data series will not be random. Such non-stationarity in the data series could be induced due to climate change for which through investigation is required.

Case-1: For demonstrating as to how the uncertainty about the system gets reduced over time, the extreme value estimates get closer to its true value as sample size increases over time, the historical data at Colaba station are catagorized into six subgroups by cumulatively adding some samples, viz. 1901–1920 ($n = 20$), 1901–1935 ($n = 35$), 1901–1950 ($n = 50$), 1901–1970 ($n = 70$), 1901–1990 ($n = 90$) and 1901–2004 ($n = 104$). EVA has been carried out using GEV distribution and return levels have been estimated for different return periods; the results are presented in Tables 2 and 3. From Table 2, it can be seen that location parameter of the GEV distribution is consistently shifting towards the right, which is somewhat obvious, whereas increase in estimated scale parameter over different data subgroups implies that over the time-scale more variation has been seen. Gumbel was the appropriate model for Colaba up to 1970, beyond which likelihood ratio (LR) test shows strong evidence against Gumbel model, which could be due to the increased variation and recording of annual maximum daily rainfall events above 400 mm too frequently for data period of the last 35 years.

Table 3 shows estimates of return levels for MRI $T = 2$, 5, 10, 50, 100, 200, 500 and 1000 years. A comparison of estimates over different data subgroups indicates that the estimates are converging to their true but unknown values as the sample size increases. Figure 1 displays the GEV density plot for different cumulative data subgroups at Colaba. The tail becomes heavier with increase in the size of the sample and probability distribution approaching the Frechet type.

Case-2: It is generally noticed that whenever extensive database is not available, EVA is based on sample size of the order of 30 years. For analysing the variability of estimates based on comparatively smaller sample size, the data are divided into three non-overlapping parts of sample size, $n = 35$, 35 and 34 years. This arrangement will also help in checking the effect of stationarity over temporal scale. EVA has been carried out using GEV distribution and return levels have been estimated for different return periods $T = 2$, 5, 10, 50, 100, 200, 500 and 1000 years, the results are presented in Tables 4 and 5. From Table 2, it can be seen that Gumbel was the appropriate model for 1901–1935 and 1936–1970, whereas LR test shows strong evidence against Gumbel model for data subgroup 1971–2004, indicating thereby that the

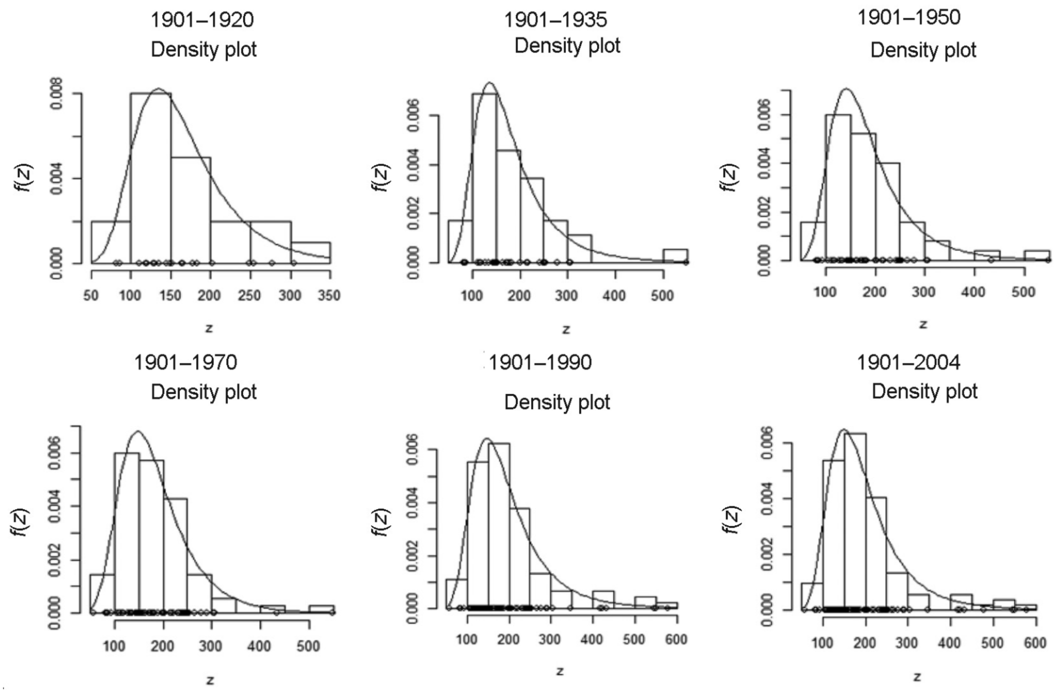

Figure 1. Generalized extreme value density plot for different cumulative data subgroups for annual maximum daily rainfall (mm) at Colaba.

Table 2. Generalized extreme value distribution fit summary for annual maximum daily rainfall (mm) at Colaba

Statistical parameter	1901–1920	1901–1935	1901–1950	1901–1970	1901–1990	1901–2004
n	20	35	50	70	90	104
Minimum	82.3	82.3	82.3	58.6	58.6	58.6
Maximum	304	548.1	548.1	548.1	575.6	575.6
Location (μ)	137.44	144.28	149.16	150.74	155.09	157.71
Scale (σ)	44.80	50.99	52.55	54.25	57.96	57.40
Shape (γ)	0.07	0.17	0.14	0.05	0.15	0.14
P value for likelihood-ratio test H_0: $\gamma = 0$	0.73, does not reject Gumbel hypothesis	0.13, does not reject Gumbel hypothesis	0.14, does not reject Gumbel hypothesis	0.46, does not reject Gumbel hypothesis	0.02, rejects Gumbel hypothesis	0.01, rejects Gumbel hypothesis

Table 3. Estimates of annual maximum daily rainfall (mm) using generalized extreme value distribution at Colaba

	Estimated annual maximum daily rainfall (mm)					
Return period (year)	1901–1920	1901–1935	1901–1950	1901–1970	1901–1990	1901–2004
2	154.1	163.6	168.9	170.8	176.9	179.3
5	208.3	231.7	237.0	235.4	252.5	253.5
10	246.6	284.8	288.4	280.3	310.0	309.5
20	285.3	342.7	343.2	325.0	371.5	369.1
50	338.3	429.3	422.9	385.5	461.6	455.6
100	380.4	504.0	489.9	432.7	537.7	528.3
200	424.4	588.1	563.6	481.5	621.9	608.1
500	485.8	715.9	672.6	548.7	747.2	726.1
1,000	534.9	827.0	764.9	601.7	853.8	825.8

observed frequency pattern of first two data subgroups is completely different from the third data subgroup. The computed 100-year annual maximum 1-day precipitation for these three data subgroups is 504.0, 384.7 and 1133.2 mm respectively.

The comparatively higher values of return level in the third data subgroup can possibly be due to the higher values of standard errors of model parameters. Therefore, if we assume that data collection was initiated in 1971, which is true for many meteorological stations in India,

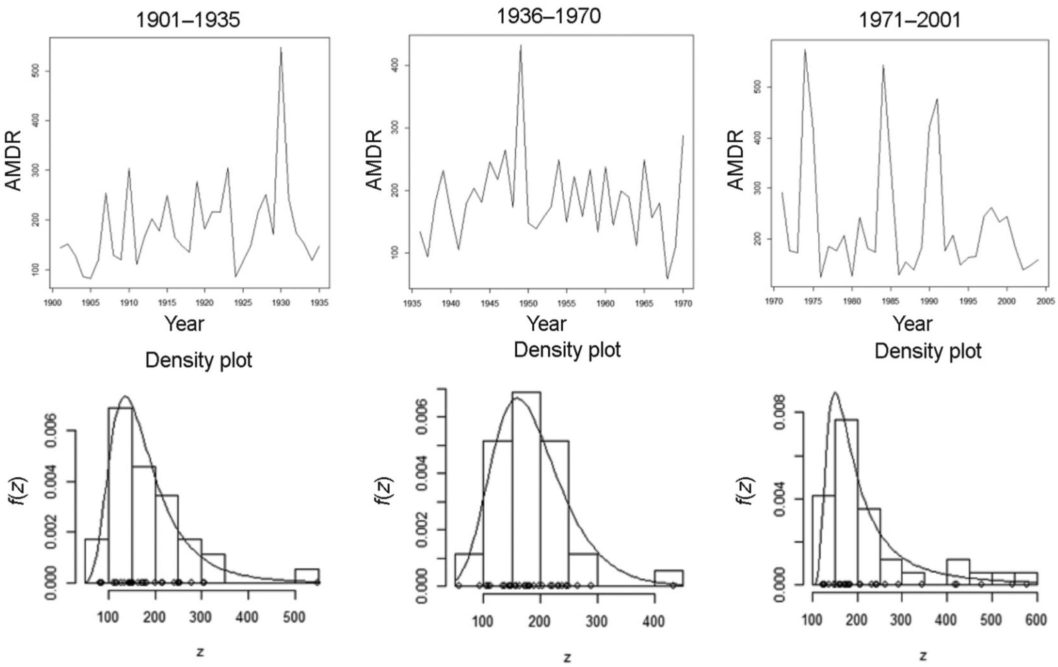

Figure 2. Scatter plot and generalized extreme value density plot for different data subgroups for annual maximum daily rainfall (mm) at Colaba.

Table 4. Fitting of generalized extreme value distribution to three non-overlapping data subgroups for annual maximum daily rainfall (mm) at Colaba

Statistical parameter	1901–1935	1936–1970	1971–2004
n	35	35	34
Minimum	82.3	58.6	123.5
Maximum	548.1	432.8	575.6
Location (μ)	144.28	156.85	168.79
Scale (σ)	50.99	55.31	46.83
Shape (γ)	0.17	–0.05	0.54
P value for likelihood–ratio test H_0: $\gamma = 0$	0.13, does not reject Gumbel hypothesis	0.61, does not reject Gumbel hypothesis	0.0002, rejects Gumbel hypothesis

Table 5. Estimates of annual maximum daily rainfall (mm) using generalized extreme value distribution at Colaba

	Annual maximum daily rainfall (mm)								
	1901–1935			1936–1970			1971–2004		
Return period (year)	Estimate	95% CI		Estimate	95% CI		Estimate	95% CI	
2	163.6	141	186	176.9	155	199	187.8	164	212
5	231.7	192	271	236.8	207	267	277.3	212	343
10	284.8	221	348	274.7	235	314	375.4	234	517
20	342.7	241	444	309.8	258	362	515.7	225	806
50	429.3	250	608	353.3	280	427	801.3	117	1,486
100	504.0	241	767	384.7	291	479	1,133.2	–109	2,376
200	588.1	214	962	414.9	297	533	1,616.1	–565	3,798
500	715.9	146	1,286	453.3	300	607	2,608.4	–1,810	7,027
1,000	827.0	61	1,593	481.1	298	664	3,765.5	–3,606	11,137

the estimates of different T-year storms based on the last data subgroup are completely different from the actual one. The scatter plot for three data subgroups in Figure 2 shows that there is only one historical peak above 400 mm for 1901–1935 and 1936–1970, whereas there are three such peaks in case of data subgroup 1971–2004 leading to heavy tail in the density plot. This also could be one of the reasons for comparatively high return levels

Table 6. Generalized extreme value distribution fit summary for annual maximum daily rainfall (mm) at Colaba

Statistical parameter	1901–1950	1951–2000
n	50	50
Minimum	82.3	58.6
Maximum	548.1	575.6
Location (μ)	149.18	168.73
Scale (σ)	52.56	64.05
Shape (γ)	0.14	0.14
P value for likelihood-ratio test H_0: $\gamma = 0$	0.14, does not reject Gumbel hypothesis	0.08, does not reject Gumbel hypothesis

Table 7. Estimates of annual maximum daily rainfall (mm) using generalized extreme value distribution at Colaba

	Annual maximum daily rainfall (mm)					
	1901–1950			1951–2000		
Return period (year)	Estimate	95% CI		Estimate	95% CI	
2	168.9	150	188	192.8	170	215
5	237.0	204	270	275.3	236	314
10	288.4	238	339	337.4	278	397
20	343.2	264	422	403.3	314	493
50	422.9	287	558	498.7	352	645
100	489.9	294	686	578.6	373	784
200	563.6	290	837	666.1	386	946
500	672.6	265	1,081	795.1	387	1,203
1,000	764.9	226	1,304	903.9	373	1,435

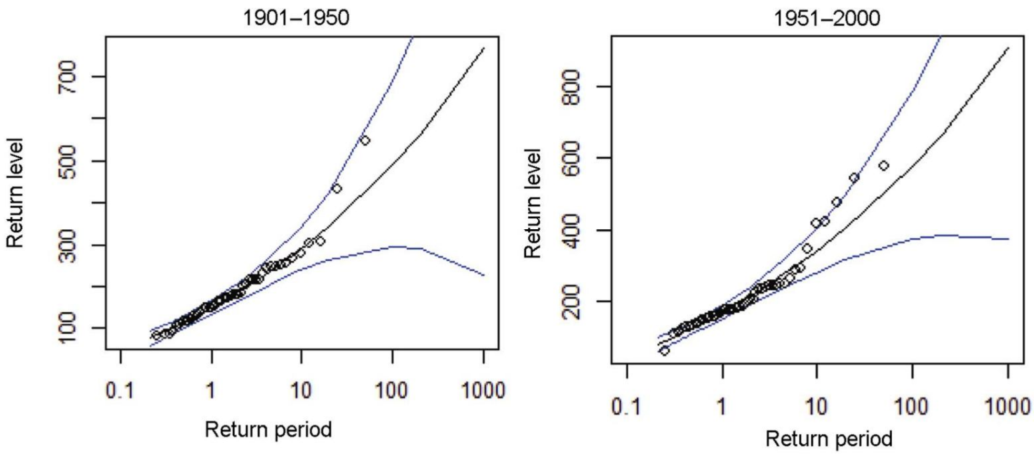

Figure 3. Return-level plot using generalized extreme value distribution for data subgroups 1901–1950 and 1951–2000 for annual maximum daily rainfall (mm) at Colaba.

in the third data subgroup. The underlying meteorological process behind the annual peak storms at Colaba has not remained stationary over temporal scale. Whether this is an evidence for climate change during the period of the third data subgroup, however, needs further detailed study.

Case-3: In case-2, EVA was carried by keeping size of the samples around 35 and different results were obtained for different subgroups of the same station data. In real life situations, we frequently come across cases where size of the sample is in the order of 50. For studying the behaviour in such situations, in case-3, historical data have been divided into two non-overlapping subgroups 1901–1950 and 1951–2000, with sample size 50 each and continuity of the data series has also been maintained. EVA with GEV distribution shown in Tables 6 and 7 indicates that LR test has not rejected Gumbel hypothesis for both the data subgroups, 1901–1950 and 1951–2000. Table 7, however, indicates that the estimated values of

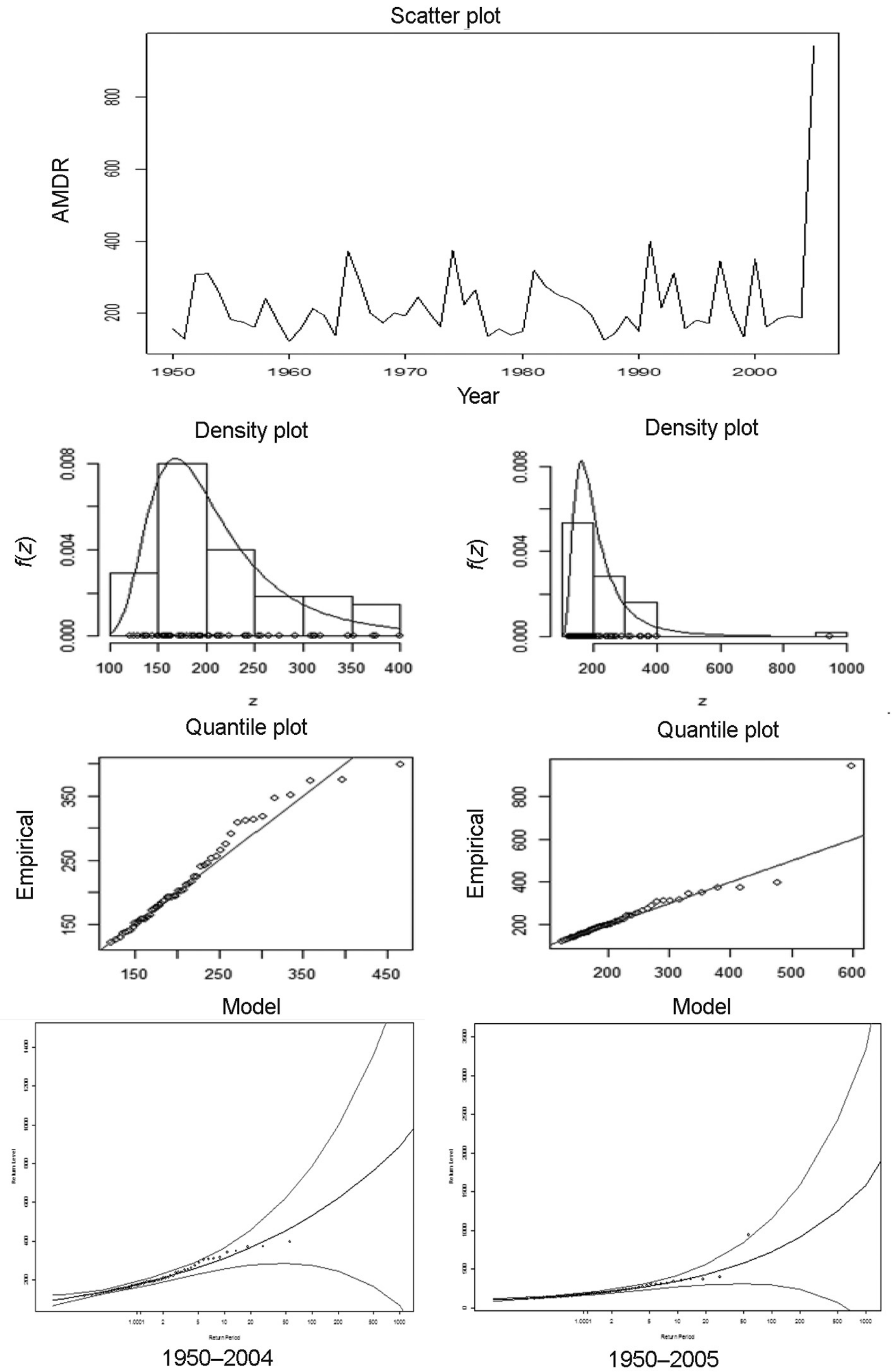

Figure 4. Scatter, density, QQ and return-level plots using generalized extreme value distribution for data 1950–2004 and 1950–2005 for annual maximum daily rainfall (mm) at Santacruz.

annual maximum daily rainfall for different return periods based on data subgroup 1951–2000 are consistently higher than those based on data subgroup 1901–1950. The return-level plot showing the estimated values of annual daily rainfall extremes for different return periods based on data subgroups 1901–1950 and 1951–2000 along with 95% CI is given in Figure 3. It indicates that GEV fit based on data subgroup 1901–1950 is better than that based on 1951–2000.

Case-4: On 26 July 2005, the Santacruz station recorded very heavy rainfall totalling 944.2 mm in a period of

Table 8. Generalized extreme value distribution fit summary for annual maximum daily rain fall (mm) at Santacruz

Statistical parameter	1950–2004	1950–2005
n	55	56
Minimum	121.2	121.2
Maximum	399.0	944.2
Location (μ)	176.52	175.51
Scale (σ)	45.74	47.17
Shape (γ)	0.21	0.35
P value for likelihood-ratio test H_0: $\gamma = 0$	0.11, does not reject Gumbel hypothesis	0.0001, rejects Gumbel hypothesis

Table 9. Estimates of annual maximum daily rainfall (mm) using generalized extreme value distribution at Santacruz

	Annual maximum daily rainfall (mm)					
	1950–2004			1950–2005		
Return period (year)	Estimate	95% CI		Estimate	95% CI	
2	193.9	177	211	194.0	176	212
5	257.2	227	287	268.9	230	307
10	308.2	257	360	338.0	266	410
20	365.3	277	453	424.1	294	554
50	453.3	286	620	573.6	309	838
100	531.6	276	787	723.0	293	1,153
200	621.9	247	997	913.7	238	1,590
500	763.3	168	1,359	1,249.2	70	2,429
1,000	889.8	69	1,711	1,586.1	–168	3,341
10,000	1,471.1	–644	3,587	3,539.0	–2,371	9,449

24 h, much higher than the PMP of 700 mm for the region, indicating that the July 2005 rainfall was an extraordinary high natural event. For assessing the impact of this event on extreme value estimates, EVA of the data at Santacruz station has been carried by excluding the July 2005 rainfall (1950–2004, $n = 55$ years) and by including July 2005 rainfall (1950–2005, $n = 56$ years) using GEV distribution. Table 8 gives the summary of fitting results, whereas Table 9 gives estimated annual maximum daily rainfall for return periods $T = 2$, 5, 10, 50, 100, 200, 500, 1000 and 10,000 years. While excluding July 2005 event of 944.2 mm daily rainfall, LR test accepts Gumbel model, whereas when the extraordinary event was considered in the analysis, LR test inferred strong evidence against the Gumbel model.

The diagnostics plots for fitting GEV distribution for annual maximum daily rainfall (mm) in Santacruz are shown in Figure 4. Unusual effect of July 2005 event is evident from these plots. If the event of 944.2 mm is interpolated from Figure 4, it can be seen that it has a MRI of 1298 years while excluding it in the analysis, whereas it has a MRI of only 221 years when the EVA is carried out by including it in the analysis. It is therefore difficult to decide as how to treat such extraordinary events in the EVA. Such behaviour similar to outliers could probably have emerged from extremely rare meteorological processes having a localized scale.

Conclusion

The effect of historical record length and impact of recent past records on extreme value estimates has been analysed using GEV model through case studies on annual maximum daily rainfall at Colaba and Santacruz. Some of the findings are given below:

1. Extreme value estimates of environmental parameters gets stabilized with increase in record length. Large sampling uncertainty is observed (as shown by width of confidence intervals) despite the theoretical rationale for the GEV model in EVA.
2. Comparatively more recorded events with higher magnitude and more variation are seen during the recent past, indicating strong evidence against the Gumbel model and leading to heavy tail for the fitted GEV distribution that finally resulted in comparatively higher values of environmental extremes.
3. The extraordinary heavy rainfall of 944.2 mm recorded at Santacruz on 26 July 2005 has a major impact on hydrological extremes. This observed event has completely changed the fit of the probability distribution when included in the EVA.
4. It has been found using Wald–Wolfowitz (1943) run test that the assumption of randomness, independence and stationarity of data is not fully satisfied. Hence, it

cannot be ruled out that varying estimates of parameters for this particular process (Mumbai rainfall) may be climate change-induced non-stationarity, in addition to insufficient record length.

Further studies in this field may be carried out, such as EVA by incorporating parameterization of trend in the GEV model that will help in investigating the possible temporal dependence in the data series. The effect of climate change-induced non-stationarity could be assessed, for which extensive, large-scale data analysis is needed.

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