Analysis of Monthly and Daily Annual Extreme Precipitation for Urban Vadodara

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Abstract
Human intervention due to change in landuse landcover, emission of greenhouse gases and aerosols affects local climate. Spatial analysis of long term annual rainfall and very wet days of 5 years' time window of rural and urban stations of Vadodara district reveals that urban annual rainfall is rising as compared to surrounding peri-urban and rural rainfall. One-day annual extreme rainfall is important for understanding and establishing impacts of climate change. Information about occurrence of extreme precipitation is of utmost importance for flood mitigation. One-day annual extremes and consecutive 5 day extremes are important for research in climate change.

If the likelihood or probability of occurrence of month of extreme value is known in advance, it can play, big role in preparedness of local governing bodies in tackling resulting problem due to extreme event. One-day annual extremes can give clear picture about flash flood occurrence. This study analyzes monthly one-day annual extreme values for a period of 90 years for Vadodara. It helps us to analyze the pattern of occurrence and more specifically month of occurrence for one-day extremes. GEV distribution for June, July, August, September and October month in one-day extreme annual rainfall series was fitted. Results show gradual change in pattern of occurrence for months of July and August with occurrence of one-day annual extreme gradually converging towards July.

Keywords: Annual extreme precipitation, Urbanization, Climate change, Floods.

Introduction

Precipitation is a key indicator of changing climate; therefore, impact of urban environment (land use, aerosols, thermal properties etc.) on precipitation will be increasingly important for climate diagnostics and prediction. Burian et al[2] and Huff et al[7] observed that increase of urban precipitation is related to city size, industrial nuclei generation and urban thermal effects. The changes have considerable applications related to urban design, local area forecasting, local water supplies, agricultural production and hydrologic design. There is a relationship between urbanization and extreme rainfall. Kishtawal et al[10] observed that increasing trend in frequency of heavy rainfall events over Indian monsoon region is more likely to be over regions where the pace of urbanization is faster.

Extreme rainfall is a major concern associated with flooding, damage and flood risk in cities. World Meteorological Organization (WMO) has established some extreme indices RX1day and RX5day for annual maximum precipitation sums for 1 day intervals and 5 day intervals respectively, R10mm and R20mm for number of days per year with precipitation amount 10 mm and 20 mm and R95 and R99 for precipitation amount per year above a site-specific threshold value for very and extremely wet days, calculated as the 95th and 99th percentile of the distribution of daily precipitation amounts on days with 1 mm or more precipitation. There have been statistically significant increases in number of heavy precipitation events although it is not uniform in all regions of the world[8].

As per IPCC special report "Global Warming 1.5 degree Celsius", the recorded observation shows increase in annual maximum 1-day precipitation (RX1day) and consecutive 5-day precipitation (RX5day) due to changes in global mean surface temperature changes[16]. Indian monsoon extreme rainfall changes due to impact of climate change showing increasing trend in one-day extreme rainfall over south peninsular region, Maharashtra, Gujarat, Bihar and some other isolated areas[6].

Generally, one-day annual maximum rainfall or maximum daily rainfall within each year is isolated in order to have as many extreme values as the total number of years which help us to analyze distribution of one-day maximum annual rainfall. The Gumbel[5], Generalized Extreme Value (GEV)[14], Log-normal[15] and Log-Pearson type 3[13,15] distributions have been applied to analyse one-day maximum annual rainfall by many researchers. Another reason for using this series is that if it is desired to extrapolate frequency of annual series data beyond the range of observation, there is an availability of simple theoretical basis[19]. The biggest disadvantage of this series is that secondary events in one year may exceed annual maxima of other years.

In addition, annual maximum floods observed in dry years may in some regions be very small and inclusion of these events can significantly bias the outcome of extreme value analysis[11]. In this study, the first objective is to find whether annual rainfall of urban station and extreme events differed from surrounding non-urban stations. An attempt is made to develop a new terminology for extreme value distribution.

Annual one-day maximum rainfall importance and disadvantages are universally accepted but no importance has been given to monthly one-day annual extreme rainfall which plays a significant role in studies of hydrology and climate change. Non-parametric methods like Mann–Kendall (MK) trend test and Sen's slope are universally used for detecting trend and magnitude for understanding the basic behavior. Monsoon in India is traditionally considered between June to October every year.

General Extreme Value (GEV) distribution theory has been applied on one day monthly annual extremes analysis individually for each month of monsoon period for distribution parameters to understand how distribution will vary from one month to another month. Analysis of one-day annual maximum rainfall analysis is also done to find out occurrence and frequency of month as one-day annual extreme repeated for the study period.

Study Area

The study area identified for this research is Vadodara, located in the central region of Gujarat, India. It lies within the geographical coordinates of 22° to 22.5° latitude and 73° to 73.5° longitude (Figure 1 illustrates the location of Vadodara).

As per the 2011 census, Vadodara's population was approximately 1.6 million, with the municipal boundary encompassing an area of about 159 square kilometers. The city's climate is classified as semi-arid, characterized by hot and predominantly dry conditions throughout the year, except during the southwest monsoon season. The average annual rainfall is 806 mm, primarily received during the monsoon period, with an average of 37 rainy days per year. The mean annual maximum temperature is 34.4°C, while the mean annual minimum temperature is 21.3°C.

For this study, daily rainfall data for 13 stations within Vadodara district were obtained from the State Water Data Centre (SWDC), Gandhinagar. Rain gauge stations with at least 30 years of data, extending up to 2016, were selected to ensure reliable urban and rural rainfall analysis. Based on these criteria, 9 out of the 13 stations were chosen for further analysis. Understanding urban rainfall patterns is critical for assessing economic vulnerabilities and mitigating disasters such as flash floods. Long-term analyses of extreme rainfall events are essential to identify the underlying causes of urban flooding.

Daily rainfall data spanning 1927–2016 were acquired from the India Meteorological Department (IMD) for a weather station located at 73°10′57″E longitude and 22°18′40″N latitude. Concurrently, rainfall data from SWDC (1961–2016) and the weather observatory at The Maharaja Sayajirao University of Baroda (1927–2016) were utilized to address missing data. The datasets were cross-referenced, revealing only a 5% variation for overlapping dates, enabling reliable interpolation of missing values for the IMD dataset during the study period.

Material and Methods

Spatio-Temporal Analysis: According to Alexander et al[1], very wet days (R95p) are defined as days where daily rainfall exceeds the 95th percentile of the daily rainfall data for the entire study period, considering only non-zero rainfall values for each station. The frequency of Very Wet days within each five-year time window was calculated to examine the temporal patterns of these events. Additionally, the Annual Total Wet-Day Precipitation (PRCPTOT) was computed and averaged over five-year intervals. Both datasets were graphically analyzed to investigate regional spatio-temporal patterns using the Inverse Distance Weighting (IDW) interpolation method in ArcGIS.

To gain deeper insights into urban rainfall patterns, block maxima analysis of one-day monthly and annual extreme rainfall events was conducted for the urban Vadodara station over a 90-year period. The Mann–Kendall (MK) trend test and Sen's slope estimator were employed to assess trends in the extreme rainfall data.

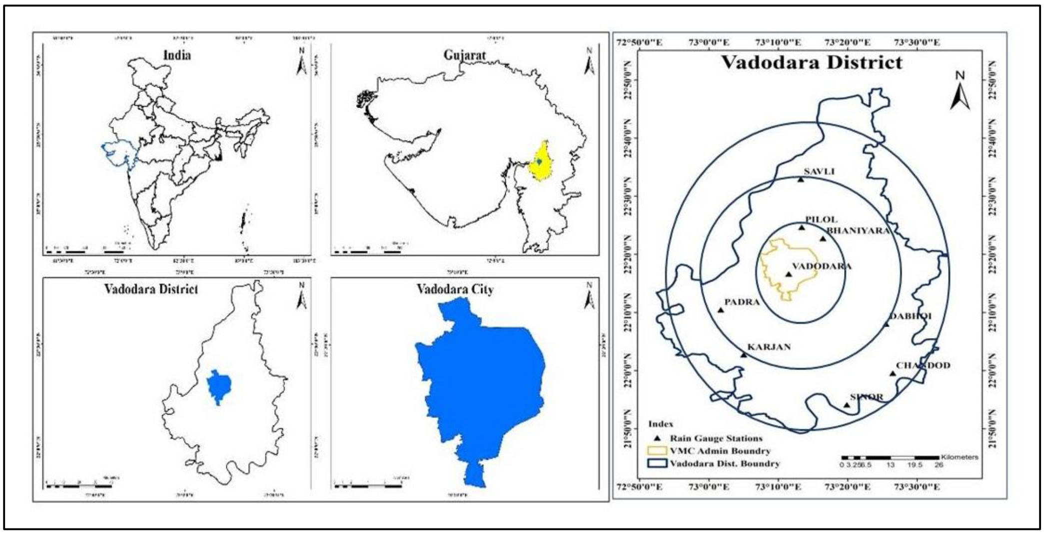

Figure 1: Study Area of Vadodara

Additionally, the Generalized Extreme Value (GEV) distribution was applied for statistical analysis and the profile-likelihood method was used to estimate confidence intervals for the GEV parameters. This comprehensive approach provides a robust understanding of rainfall variability and trends in urban Vadodara.

Trend Test: Trends are visualized through graphically and statistical hypothesis testing. Monotonic trending and no change are generally analyzed by Mann-Kendall trend test. Non-parametric test for randomness against trend was developed by Mann[12]. It is particularly an application of Kendall's test for correlation which is Kendall's tau[9]. Mann-Kendall test is generally used for detecting monotonic trend in climate or hydrologic data. The null hypothesis H_0 is that data coming from a population with independent realization is identically distributed i.e. no trend is present. Alternatively, hypothesis H_α tells whether data follows a monotonic trend. Sen's slope computes both slope (i.e. linear rate of change) and intercept[17, 18] is used to find the magnitude of trend.

General Extreme Value Theory: The Gumbel, Fréchet and Weibull families can be combined into single family of models having distribution functions of the form[4]:

$$G(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\} \tag{1}$$

It is defined on set $\left\{z: 1+\frac{\xi(z-\mu)}{\sigma} > 0\right\}$ where parameter satisfies $-\infty < \mu < \infty, \sigma > 0$ and $-\infty < \xi < \infty$. This is called Generalized Extreme Value (GEV) family distribution. The model has three parameters: scale parameter (μ), location parameter (σ) and shape parameter (ξ).

The type II and type III classes of extreme value distribution correspond respectively to the cases $\xi > 0 \; and \; \xi < 0$. Equation {10} limit $\xi \to 0$ leading to the Gumbel family with distribution.

$$G(z) = \exp\left[-\exp\left\{-\left(\frac{z-\mu}{\sigma}\right)\right\}\right], \; -\infty < z < \infty \tag{2}$$

Profile-Likelihood Interval: Unknown parameters are part of hydrology modeling, some parameters are often of interest in practice and rest of the parameters are referred to as trouble parameters. Profile-likelihood provides more accurate estimates of confidence intervals than standard intervals based on the asymptotic normality theory[3,4].

Let θ be a d-dimensional parameter vector (e.g. $\theta = (\mu, \sigma, \xi)$ for the GEV). The log-likelihood for θ is $l(\theta_i; \theta_{-i})$ where θ_{-i} indicates the parameter vector θ excluding the i-th parameter. Profile log-likelihood for θ_i is defined as:

$$l_p(\theta_i) = \max_{\theta_{-i}} l(\theta_i, \theta_{-i}) \tag{3}$$

This method is complicated as likelihood must be optimized with numerical techniques for which computation is expensive and is difficult to automate.

Results and Discussion

Spatio-Temporal Analysis: A spatial analysis of rainfall over a five-year time window was conducted to observe both spatial and temporal changes in the region. Results indicate that high annual average rainfall was observed at all stations except Padra, during the period 2001–2005 (Figure 2 i). Urban areas consistently recorded annual average rainfall exceeding 1000 mm during the periods 2001–2005, 2006–2010 and 2011–2016. The frequency of very wet days defined as days when daily rainfall exceeds the 95th percentile threshold, was also analyzed. A total of 132 very wet day events were recorded at the urban station of Vadodara, the highest among all stations, whereas the peri-urban station Bhaniyara observed the lowest count with 78 events during the study period. Notably, the number of very wet days in urban areas has been increasing since 2001 (Figure 3 i, j, k).

Spatial analysis revealed that the region's rainfall patterns are highly stochastic. Urban stations consistently displayed increasing trends in both average annual rainfall and the frequency of very wet days, underscoring the impact of urbanization on rainfall patterns. For study of urban extreme rainfall, data of five months i.e. June, July, August, September and October was considered for one-day monthly annual extreme analysis. Figure 4 shows magnitude line chart with linear trend line for each one-day monthly annual extreme analysis. The results show that the extreme values for June have decreasing trend whereas the extreme values for July, August and September have a consistently increasing trend. Extreme values for October are found to have slightly decreasing trend.

Box-plot Analysis: Box plot for each one-day monthly annual extremes with median trend is given in figure 5. Median trend line in box plots shows that July has highest median which is 76.6 as compared to 52.45 for June, it is 69.35 for August, it is 35.56 for September and for October.

Trend Test: Results for Mann-Kendell's and Sen's slope are shown in table 1. June, July, August, September and October one-day annual extremes reject null hypothesis and accept alternative at 5% significance level which means monotonic trend exists and by τ it shows that June and October have decreasing trend but July, August and September have increasing trend. Sen's slope magnitude for June month is decreasing and increasing in July, August and September but for October, it shows zero which means there is no significant change in magnitude. Since one-day annual extreme tau value obtained is very nearest to zero, it does not give a clear picture as to whether trend is increasing or decreasing, it just gives an idea that trend is monotonic which can be established using the P value. Since Sen's slope magnitude is also nearest to zero, it indicates slight or no change.

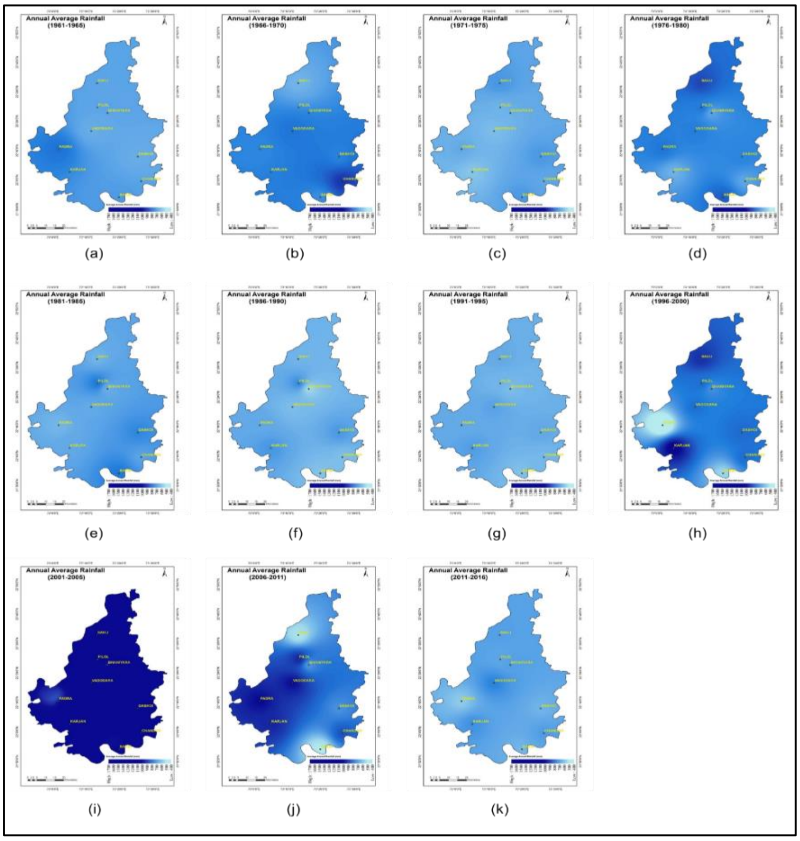

Figure 2: Average Annual Rainfall (a)1961-1965 (b) 1966-1970 (c) 1971-1975 (d) 1976-1980 (e) 1981-1985 (f) 1986-1990 (g) 1991-1995 (h) 1996-2000 (i) 2001-2005 (j) 2006-2010 and (k) 2011-2016

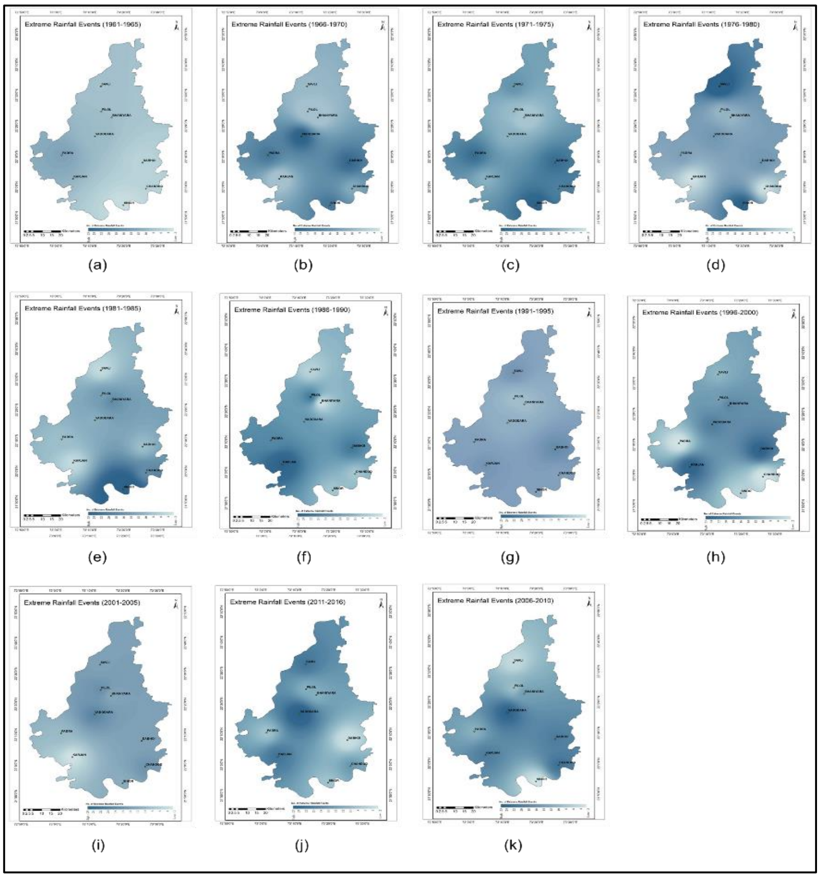

Figure 3: Extreme Rainfall Events (a)1961-1965 (b) 1966-1970 (c) 1971-1975 (d) 1976-1980 (e) 1981-1985 (f) 1986-1990 (g) 1991-1995 (h) 1996-2000 (i) 2001-2005 (j) 2006-2010 and (k) 2011-2016

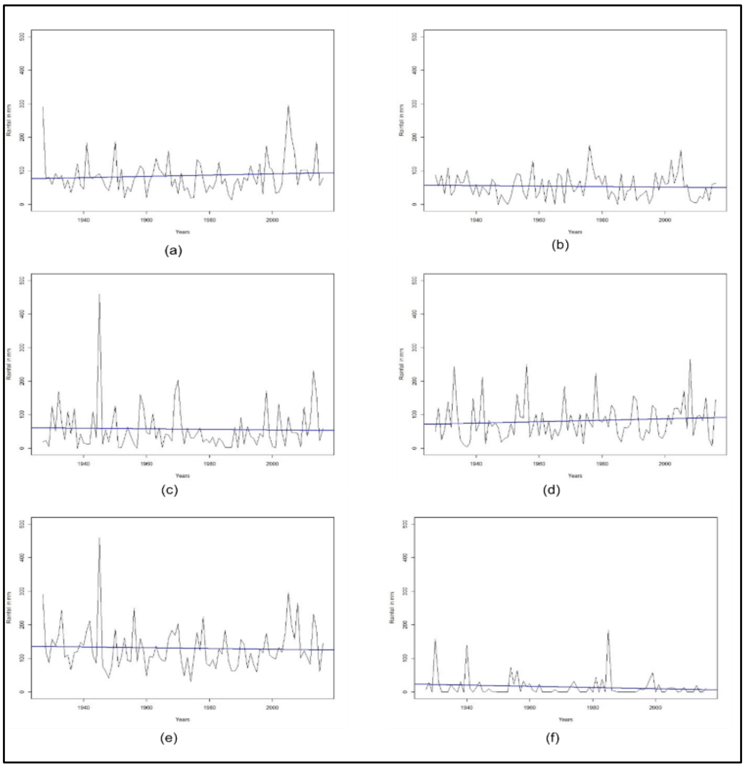

Figure 4: Magnitude plot with linear trend line. (a) June. (b) July. (c) August (d) September. (e) October and (f) One-day annual extreme rainfall

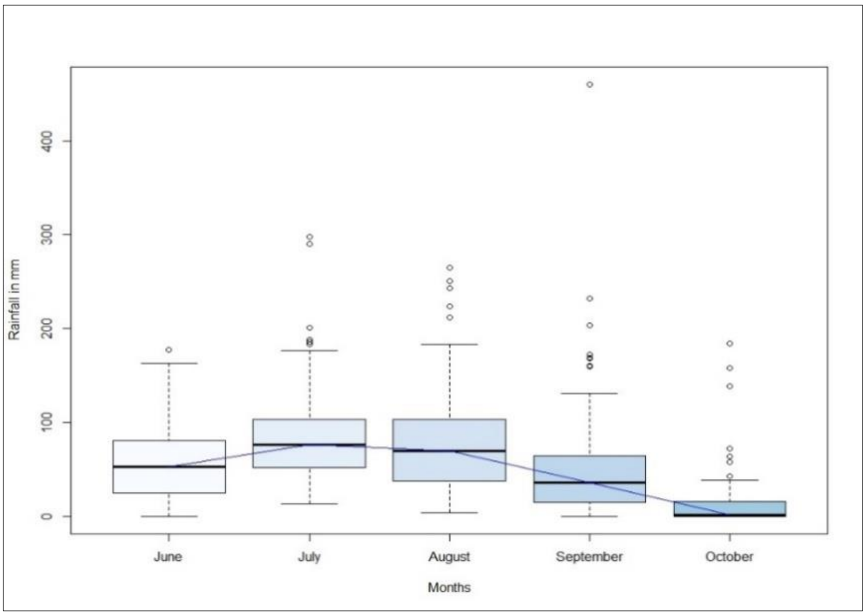

Figure 5: Box plot for each month one-day annual extremes.

Table 1
Trend test result

Months	Tau	P value	Sen's slope magnitude
June	-0.06	0.4187	-0.1145833
July	0.05	0.4814	0.1212766
August	0.11	0.1385	0.296
September	0.01	0.914	0.01363636
October	-0.09	0.2437	0
Annual	-0.00325	0.9666	-0.007792208

One-Day Annual Extreme Month Frequency: For hydrologist, it is important to understand as to when or what is the probability of occurrence of extreme value of rainfall during the year. Understanding month of occurrence of extreme value can help in the management and mitigation of flood during an extreme event. Analysis for frequency of occurrence of extreme event for June, July, August, September and October for a period of 90 years was carried out as shown in figure 6. It shows that percentage of occurrence of one-day annual extreme in July and August months is equally distributed.

Figure 7 shows graph for occurrence for one-day annual extremes plotted at 10-years interval. It is observed that after 40 years, trend lines for July and August intersect each other and both behave in opposite manner. Trend line for July shows that frequency of occurrence of extreme event has increased in July while it has decreased in August and this cross-over is experienced during the decade of 1967-1976. Frequency of occurrence for September is also found to decrease while for June, occurrence is consistent. October is depleting in extremes after 1997-2006.

The extreme value for each month was compared with one-day annual extreme value to understand differences in proportion of monthly and annual extreme values. Extreme magnitude portion percentage of each month with respect to one-day annual extremes for each year was found and frequency of that portion for each month was analyzed by dividing in classes of 10. Figure 7 shows plot of frequency with linear trend line showing the number of times, magnitude of extreme event has occurred in July which is steadily increasing along with portion.

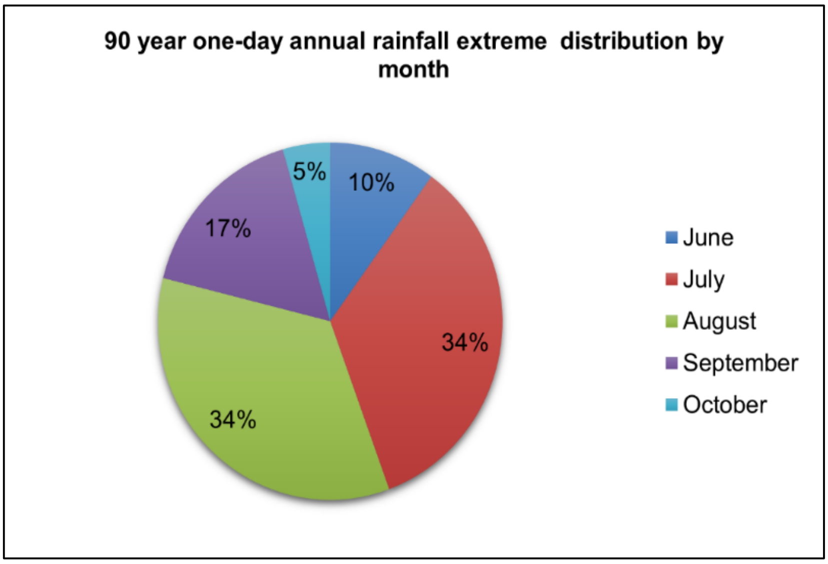

Figure 6: Ninety years one-day annual rainfall extremes distribution by month

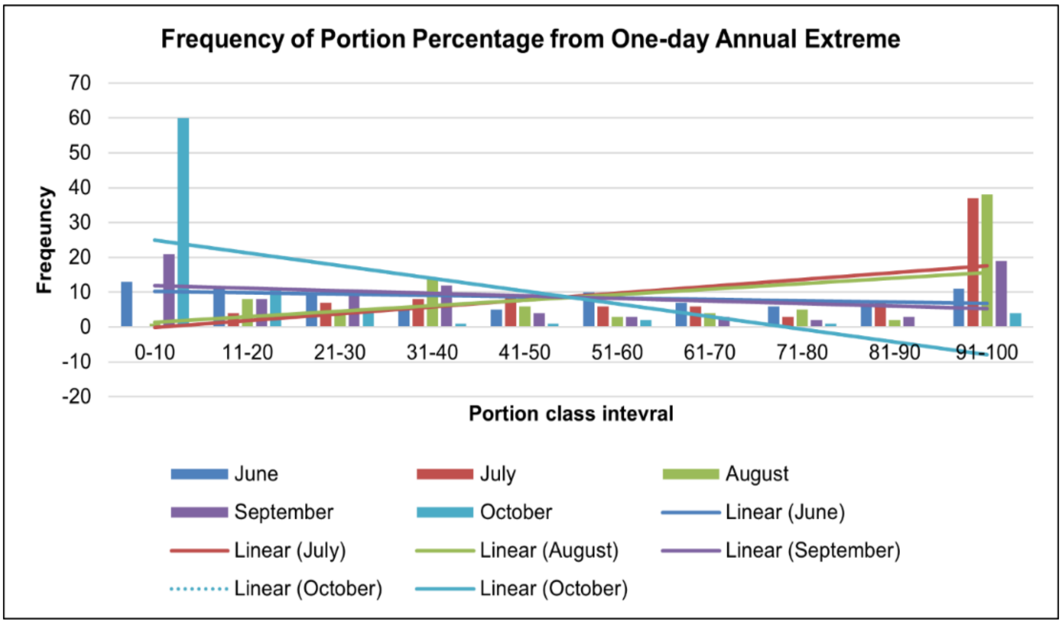

Figure 7: Extreme magnitude portion percentage of each month with respect one-day annual extreme frequency at 10% interval.

Average one-day extreme annual rainfall value is obtained as 131 mm for a study period of 90 years. Average one day monthly extreme values for each month for same study period were obtained as 54 for June, 86 for July, 82 for August, 57 for September and 15 for October. This shows that percentage of average extreme value for month of June as compared to average one-day annual extreme value of 131 is 41%, for July it is 66%, for August it is 63%, for September it is 43% and for October it is 11%.

General Extreme Value Theory and Profile-Likelihood for Parameter Confidence of Interval: GEV distribution is used for finding best fit distribution for one-day monthly annual extremes and confirmed 95% confidence of interval for shape parameter by using profile-likelihood method. Table 2 shows GEV parameter for one-day monthly annual extremes for all five months. June follows Weibull distribution as $\xi < 0$, its value is nearest to zero which means Gumbel distribution is also candidate and confidence of interval confirms that zero is included.

Similarly, August follows Fréchet as $\xi > 0$ but as its value is nearest to zero, Gumbel distribution is also candidate and confidence of interval of latter confirms that zero is included. Fréchet distribution is found to be the best fit for July, September and October as value zero does not lie in confidence of interval. One-day annual extremes are also found to follow Fréchet distribution which is also found to be followed by one day monthly annual extreme value distribution in 3 out of 5 months of monsoon season. Figure 8 shows diagnostic plot for fitting GEV distribution to each one-day monthly annual extremes including QQ plot without and with regression line between 95% confidence interval, return period and density plot.

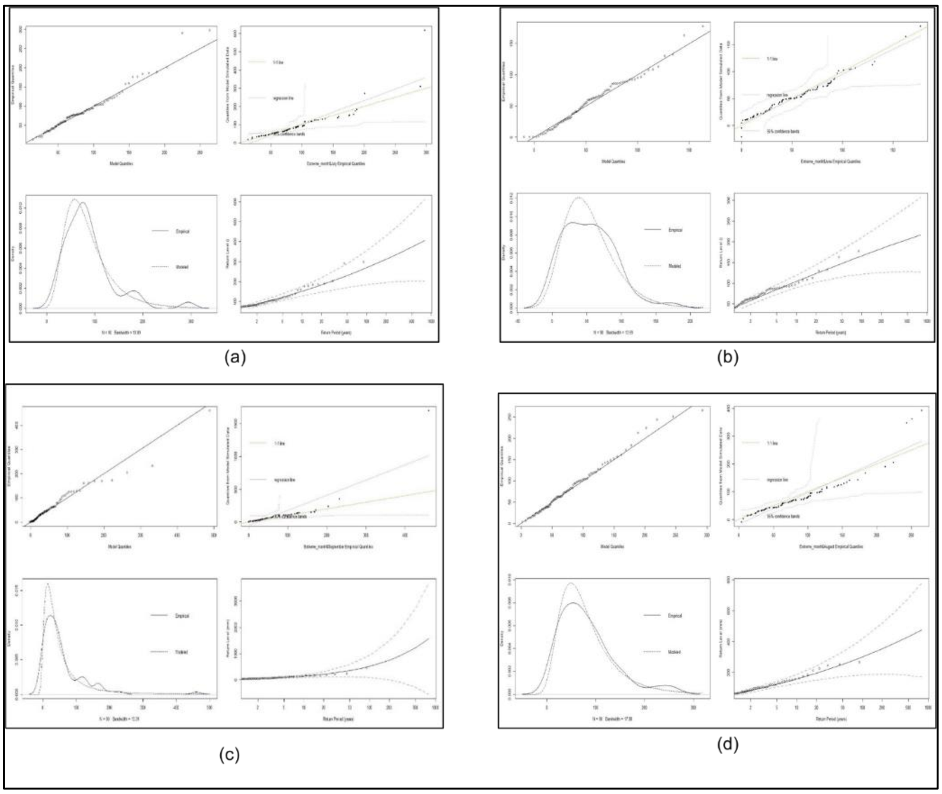

Figure 8: Plot for fitting GEV distribution to each one-day monthly annual extremes: (a) June. (b) July. (c) August. (d) September. (e) October and (f) One-day annual extremes.

Table 2
General Extreme Value Distribution (GEV) Result

Month	Location	Scale	Shape	Confidence of interval	Distribution
June	37.26952527	30.51092	-0.03896112	(-0.0646, 0.1225)	Gumbel
July	61.739839	34.03062	0.1171509	(0.0167, 0.1871)	Fréchet
August	53.868824	38.14784	0.139575	(-0.0331, 0.3059)	Gumbel
September	23.5556983	25.73519	0.5196573	(0.2939, 0.6297)	Fréchet
October	1.823173	12.78747	7.013851	NA	Fréchet
One-day annual Extremes	100.2924187	43.4129	0.1056873	(0.0906, 0.2614)	Fréchet

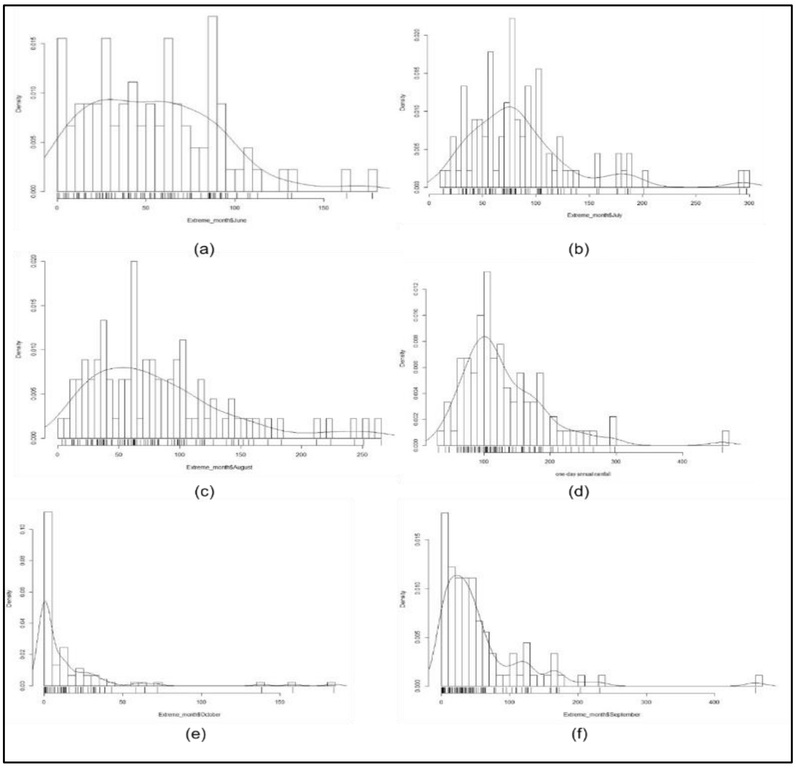

Figure 9: Histograms with normal density line graph: (a) June. (b) July. (c) August. (d) September. (e) October and (f) One-day annual extremes.

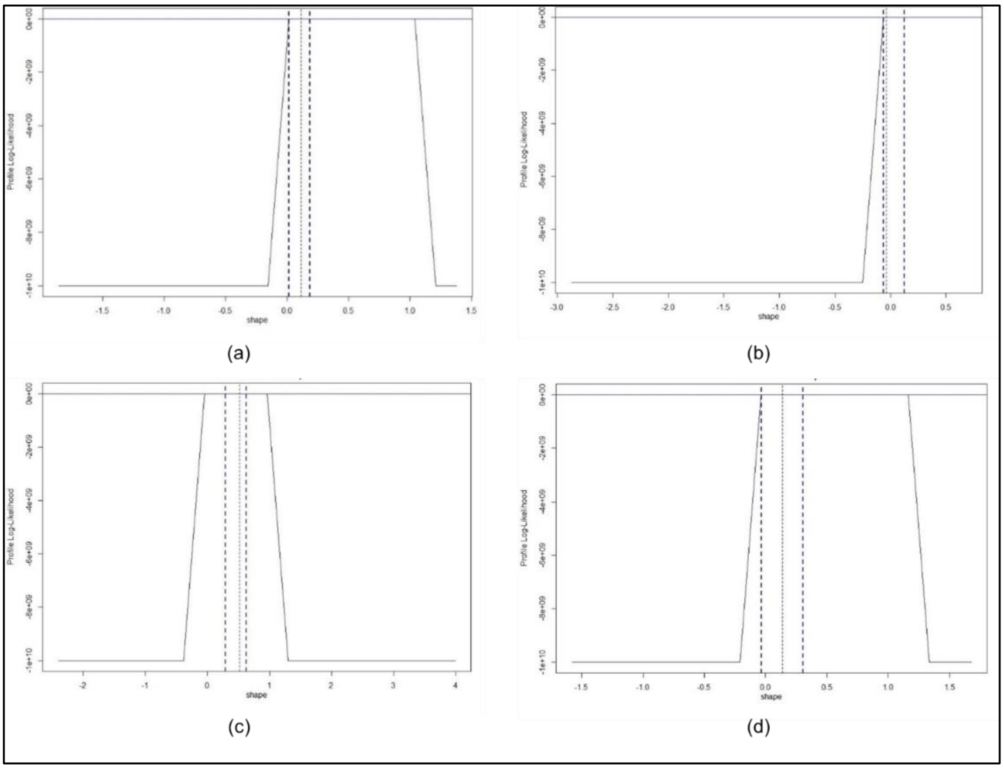

Figure 10: Profile likelihood graph: (a) June. (b) July. (c) August. (d) September

Histograms plots with normal density line graph to analyze above density plot for each month one-day annual extremes were prepared as in figure 9. It is difficult to get the exact profile likelihood graph for particular fit. However, vertical dashed lines representing the upper and lower confidence interval range and shape parameter line can be plotted for a better idea. Figure 10 shows all profile likelihood graph for each one-day monthly annual extremes shape parameter. While the graphs for June, July, August and September can be plotted, the confidence of interval of October month cannot be plotted as the shape parameter is more than 1 which is beyond the range of 95% confidence interval.

Conclusion

The spatial analysis highlighted the highly stochastic nature of rainfall patterns in the region. Urban Vadodara demonstrated a clear upward trend in both annual average rainfall and the occurrence of very wet days, emphasizing the influence of urbanization on altering local rainfall dynamics. One of the primary focuses in climatology studies is assessment of extreme precipitation for preventing loss of human lives and material damage. While lot of research is already done or is being done on one-day annual extreme precipitation, it is equally important to understand where this extreme value falls.

If likelihood or probability of occurrence of month of extreme value is known in advance, it can help local governing bodies in tackling resulting problem. Many cities witness heavy rainfall events for more than once in the year during monsoon. Understanding that each month of monsoon can have an extreme event which can be a potential flood is very important and necessary because a flood, is a complex phenomenon which can be a result of multiple consecutive extreme events. It is very rare that a single extreme scattered event has resulted in a heavy flood.

One-day monthly annual extremes analysis helps us for better understanding about each month one-day extremes as well as annual extremes. Results show that for majority of the months, the magnitude of one-day monthly annual extremes series shows significant increasing trend which goes unnoticed by using only one-day annual extremes plots. Majority of months follow Fréchet distribution for one-day monthly annual extremes while one-day annual extreme values also follows Fréchet distribution. Magnitude of extreme events has reduced for June, significantly increased in July and August with slight increase in September. No change has been observed in the magnitudes of the extreme events for the month of October.

The analysis of a 90-year data shows that while August was one of the strongest months in the initial 10 years for the occurrence of one-day extremes frequency but the frequency of occurrence of an extreme event in August goes on decreasing while that of the month of July goes on increasing. The trend lines for the months of July and August cross each other during the decade of 1967-1976 years. During this decade, it is observed that the frequency of occurrence of an extreme event in July and August is almost equal. However, after that, the frequency of occurrence of an extreme event in August starts depleting while that of the month of July starts increasing. The frequency of occurrence of an extreme event in the months of June, September and October has reduced and therefore they can be considered as considerably safer months for handling impacts of floods.

During the study period of 90 years, the trend lines of the frequency of occurrence for the months of July and August have crossed each other at a threshold of 45 years. The frequency of the magnitude of the extreme rainfall for the months of July and August falling in the range of 91-100 % of the one-day annual extreme is 37 and 38 respectively with July showing the rising trend. The study clearly established an impact of climate change on the magnitude as well as the occurrence of the one-day annual extreme rainfall. It also shows that the occurrence of the one-day annual extreme is gradually converging towards the month of July for the monsoon season. It needs to be seen as to how the trends of the frequency and magnitude for the months of July and August will behave in future and whether they would cross again in future.

Acknowledgement

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