# Analyzing Non-stationarity in the Hyderabad City Rainfall Intensity-Duration-Frequency Curves

V. Agilan and N.V. Umamahesh

Abstract The infrastructure design is primarily based on rainfall intensityduration-frequency (IDF) curves and the current IDF curves are based on the concept of stationary extreme value theory (i.e. occurrence probability of extreme precipitation is not expected to change significantly over time). But, the extreme precipitation events are increasing due to global climate change and questioning the reliability of our current infrastructure design. In this study, the trend in Hyderabad city 1-, 2-, 3-, 6-, 12-, 24- and 48-h duration annual maximum rainfall series are analyzed using the Mann–Kendall (M–K) test, and a significant increasing trend is observed. Further, based on recent theoretical developments in the extreme value theory (EVT), non-stationary rainfall IDF curve for the Hyderabad city is developed by incorporating linear trend in the location parameter of the generalized extreme value (GEV) distribution. The study results indicate that the IDF curves developed under the stationary assumption are underestimating the precipitation extremes.

Keywords Extreme rainfall  $\cdot$  IDF curves  $\cdot$  Hyderabad city  $\cdot$  Non-stationarity

# **Introduction**

The rainfall intensity-duration-frequency (IDF) curves are commonly used in storm water management and other engineering design applications across the world (Endreny and Imbeah [2009](#page-8-0)) and these curves are developed based on historical rainfall time series data by fitting a theoretical probability distribution to annual maximum rainfall series or partial duration series (Cheng and AghaKouchak [2014\)](#page-7-0). The existing IDF curves are based on the concept of stationary extreme value theory (i.e. occurrence probability of extreme precipitation is not expected to change significantly over time  $(Jakob 2013)$  $(Jakob 2013)$  $(Jakob 2013)$ ). However, in recent years, the extreme

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precipitation events are escalating due to global climate change (Tramblay et al. [2012;](#page-8-0) Xu et al. [2015](#page-8-0)). In specific, in recent years, the impact of different climate processes on the changes in daily extreme precipitation has been analyzed, such as el niño-southern oscillation (ENSO) cycle (Revadekar and Kulkarni [2008](#page-8-0); Agilan and Umamahesh [2015a](#page-7-0)), Global warming (Kunkel et al. [2013;](#page-8-0) Villafuerte and Matsumoto [2015\)](#page-8-0). Furthermore, reasonable literature reported the possible changes in precipitation due to urbanization (Kishtawal et al. [2009\)](#page-8-0). Especially Burian and Shepherd ([2005\)](#page-7-0) hypothesized the possible role of urbanization in diurnal rainfall distribution. In addition, recent studies reported the influence of urbanization in extreme rainfall events as well (Lei et al. [2008;](#page-8-0) Miao et al. [2011](#page-8-0)).

Hence, the various physical processes (discussed in the above paragraph) are expected to alter the intensity, duration and frequency of rainfall extremes over time. Consequently, the time series will have a non-stationary component in it and the IDF curves developed based on the stationary extreme value theory may underestimate the extreme event. In other words, the future extreme rainfall events that exceed the capacity of existing drainage systems may occur more frequently if the drainage is designed based on the concept of stationary extreme value theory (Zahmatkesh et al. [2015](#page-8-0)). In addition, urban flooding and the damage to infrastructure and society are problems in both developing and developed countries. Therefore, the non-stationarity in the rainfall IDF curves of an urban area needs to be analyzed for better urban flood management. In this study, the non-stationarity (trend) in the Hyderabad city extreme rainfall series is analyzed using the Mann– Kendall (M–K) test. Further, based on recent theoretical developments in the extreme value theory (EVT), non-stationary rainfall IDF curve for the Hyderabad city is developed by incorporating linear trend in the location parameter of the generalized extreme value (GEV) distribution and they are compared with stationary IDF curves.

#### Study Area and Data

The Hyderabad city is the capital of the state of Telangana in India. Location map of the Hyderabad city is shown in Fig. [1.](#page-2-0) The Hyderabad city lies between the latitudes of 17.25°N and 17.60°N and longitudes of 78.20°E and 78.75°E and situated at a height of about 500 m above the mean sea level. It is classified as a semi-arid region and the Köppen–Geiger classification is BSh (Peel et al. [2007\)](#page-8-0). The major urbanization of Hyderabad city took place after 1990. During 1971–1990, the average rainfall of Hyderabad city was 796 mm per year. But, it has increased to 840 mm per year during 1991–2013. The wettest month of the city is August and the average rainfall in this month is 163 mm.

For this study, the hourly observed rainfall data for Hyderabad city is procured from the India Meteorological Department (IMD) for the period of 1 January

<span id="page-2-0"></span>

Fig. 1 Location map of Hyderabad city (Agilan and Umamahesh [2015b\)](#page-7-0)

1972–31 December 2013 (42 years). This data is gauge observation and it is observed at the centre of Hyderabad city, i.e. 78.46°E and 17.45°N. The location of this gauge is given in Fig. 1 (star mark).

## Methodology

The methodology of this study comprises of following two sections,

- 1. Analyzing the trend present in the annual maximum rainfall series of 1-, 2-, 3-, 6-, 12-, 24- and 48-h duration using the Mann–Kendall test.
- 2. Developing non-stationary rainfall IDF relationship for the Hyderabad city.

#### Trend Analysis

Statistical tests that are used to detect trends in time series are broadly classified into two groups: parametric and nonparametric methods. As the hydrometeorological time series data are generally non-normally distributed and censored, the nonparametric tests are most appropriate for hydrometeorological time series (Bouza-Deaño et al. [2008](#page-7-0)). The nonparametric Mann–Kendall (M–K) test (Mann [1945;](#page-8-0)

Kendall [1962\)](#page-8-0) for trend analysis have a long tradition of use in hydrology and have been applied in the case of extremes (Villarini et al. [2009](#page-8-0); Cheng and AghaKouchak [2014\)](#page-7-0). Thus, in this study, the MK test is used to detect trends in annual maximum rainfall intensity of the selected storm durations (i.e. 1, 2, 3, 6, 12, 18, 24, 36 and 48 h). The power of the MK test depends on pre-assigned significance level, the magnitude of the trend, sample size and the amount of variations within the time series (Yue et al. [2002\)](#page-8-0).

In addition, the MK test is free of normally distributed data assumption, but data independency remains as an assumption of this test. Thus, the MK test rejects the null hypothesis of no trend more often than that specified by the significance level  $\alpha$ when the data are serially correlated (von Storch [1995](#page-8-0)). If the time series has significant lag-one autocorrelation, the series should be pre-whitened before applying the MK test to avoid the effect of serial correlation (von Storch [1995;](#page-8-0) Bayazit and Önöz [2007\)](#page-7-0). The method proposed by von Storch ([1995\)](#page-8-0) to pre-whitening the series is given as follows (Eqs.  $(1)$ – $(3)$ ):

$$
x_i' = x_i - \rho x_{i-1} \tag{1}
$$

$$
\rho = \frac{\frac{1}{n-1} \sum_{i=1}^{n-1} (x_i - E(x_i))(x_{i+1} - E(x_i))}{\frac{1}{n} \sum_{i=1}^{n} (x_i - E(x_i))^2}
$$
(2)

$$
E(x_i) = \frac{1}{n} \sum_{i=1}^{n} x_i
$$
 (3)

where x' is pre-whitened data series, x is original series and n is the size of data series. If the original series has significant lag-one autocorrelation, the MK test is applied to pre-whitened data series. Otherwise, the MK is applied to the original data series.

#### The Non-stationary IDF Curves

Consider an annual maximum series of n independent and identically distributed (iid) random variable  $x_1, x_2,...,x_n$ . The annual maximum series converges to generalized extreme value (GEV) distribution and the cumulative distribution function is given by Eq.  $(4)$  (Coles [2001](#page-7-0)).

$$
F(x; \mu, \sigma, \xi) = \exp\left\{-\left[1 + \frac{\xi(x - \mu)}{\sigma}\right]^{-1/\xi}\right\}, \quad \sigma > 0, 1 + \frac{\xi(x - \mu)}{\sigma} > 0, \quad \xi \neq 0
$$
  

$$
\exp\left\{-\exp\left[-\frac{(x - \mu)}{\sigma}\right]\right\}, \quad \sigma > 0, \quad \xi = 0
$$
 (4)

where  $\mu$ ,  $\sigma$  and  $\zeta$  are; location, scale and shape parameters of the GEV distribution, respectively. As the precise estimation of shape parameter is difficult, it is unrealistic to assume it as a smooth function of time (Coles [2001](#page-7-0)) and modelling temporal changes in scale parameter ( $\sigma$ ) requires long-term observations (Cheng et al. [2014\)](#page-7-0). Thus, the scale and shape parameters are kept constant and the non-stationarity is introduced only in the location parameter of GEV. The non-stationary setting for the location parameter of the GEV as a function of the covariate  $(f(T))$  is given by Eq. (5).

$$
\mu(t) = \begin{bmatrix} 1 & f(T) \end{bmatrix} \begin{bmatrix} \mu_0 \\ \mu_1 \end{bmatrix} \tag{5}
$$

The slope parameters  $\mu_1$  represent the trend in the location parameter due to the covariate  $f(T)$ . For computational simplicity,  $f(T)$  must be standardized before non-stationary setting. As an approximation, the linear trend is often used to represent a long-term trend (Cheng et al. [2014](#page-7-0); Cheng and AghaKouchak [2014;](#page-7-0) Yilmaz and Perera [2014](#page-8-0)). In particular, Sugahara et al. ([2009\)](#page-8-0) analyzed the non-stationarity in the extreme daily rainfall in the Sao Paulo city, Brazil by introducing linear trend in scale parameter of the Generalized Pareto distribution. Cheng and AghaKouchak [\(2014](#page-7-0)) developed a non-stationary rainfall IDF curves by incorporating linear trend in the location parameter of the GEV distribution. Yilmaz and Perera ([2014\)](#page-8-0) investigated the non-stationarity in the IDF curves of Melbourne, Australia by incorporating linear trend in location and shape parameters of the GEV distribution. The covariate for linear trend in the location parameter of the GEV is given by Eq.  $(6)$ .

$$
f(T) = T \tag{6}
$$

where  $T = 1, 2, 3...$  n (n is the size of the annual maximum rainfall series). In this study, the parameters of the non-stationary GEV distribution are estimated by the method of maximum likelihood, as the method of maximum likelihood can be easily extended to the non-stationary case (Coles [2001;](#page-7-0) Katz [2013](#page-8-0)). The non-stationary rainfall intensity is estimated using the model parameters of the non-stationary GEV model. But, unlike the stationary model, the location parameter value will vary over the time. In this study, the low risk (more conservative) approach (Cheng et al. [2014](#page-7-0)) is used to calculate location parameter value, i.e. the 95 percentiles of the location parameter values and it is given by Eq. (7). The 95 percentiles of the location parameter value give the effective return level (Cheng et al. [2014](#page-7-0)).

$$
\widehat{\mu}_{95} = Q_{95}(\widehat{\mu}_{t1}, \widehat{\mu}_{t2}, \dots, \widehat{\mu}_{t100},)
$$
\n(7)

Estimation of  $1/p$  return level is given by Eq.  $(8)$  $(8)$  (Coles  $2001$ ; Cheng et al. [2014\)](#page-7-0).

$$
z_T = \begin{cases} \n\hat{\mu} + \frac{\hat{\varphi}}{\hat{\xi}} \left[ (-\log(1-p))^{-\hat{\xi}} - 1 \right], & \hat{\xi} \neq 0 \\ \n\hat{\mu} + \hat{\sigma} [-\log(-\log(1-p))], & \hat{\xi} = 0 \n\end{cases} \tag{8}
$$

<span id="page-5-0"></span>where  $p$  (the exceedance probability) is the frequency (i.e. how frequently an extreme rainfall of specified intensity and duration is expected to occur).

#### Results and Discussion

Before analyzing the trend present in the annual maximum rainfall series of 1-, 2-, 3-, 6-, 12-, 24- and 48-h duration using the MK test, the presence of serial correlation in the rainfall series are analyzed. Significant lag-one autocorrelation is detected in the data series of 1-, 24- and 48-h rainfall durations. The remaining rainfall durations do not show any statistically significant lag-one autocorrelation and they are considered to be independent series. Then the autocorrelated series (i.e. 1-, 24- and 48-h durations rainfall series) are pre-whitened using the method discussed in Sect. [4.1.](#page-2-0) The MK test is then applied to the pre-whitened 1-, 24- and 48-h duration time series and the original data sets of the remaining rainfall durations (i.e.  $2-$ ,  $3-$ ,  $6-$  and  $12-h$ ). Table 1 shows the results of MK test with different duration annual maximum rainfall series. The 'Tau' value of the MK test is similar to correlation coefficient and its value varies from −1 to 1 (i.e. positive Tau value indicate increasing trend and negative Tau value indicate decreasing trend).

In this study, all duration rainfall series are having positive Tau value and it indicates that the annual maximum rainfall series of all duration (i.e. 1-, 2-, 3-, 6-, 12-, 24- and 48-h) are having increasing trend. The two-tailed p-value given in Table 1 indicates that the increasing trend present in the 12-h duration rainfall series is statistically significant at 0.05 significance level, and the increasing trend present in the 6- and 48-h duration rainfall series is statistically significant at 0.1 significance level. The increasing trend in remaining duration data series is not significant at 0.1 significance level. In addition, the previous studies indicate that the precipitation extremes in several regions of the world have increased (Westra et al. [2013\)](#page-8-0).



But, most ground-based stations do not exhibit a strong trend and only limited stations show a statistically significant non-stationary behaviour (Westra et al. [2013;](#page-8-0) Cheng and AghaKouchak [2014\)](#page-7-0). Moreover, the purpose of analyzing trend using the MK test is to avoid implementing a time varying extreme value analysis on a data that does not show a significant change in extremes over time. The recent studies highlight the need to go beyond subjective criteria for significance analysis, especially in a non-stationary world (Rosner et al. [2014\)](#page-8-0). Thus, the non-stationarity can be applied to all data sets regardless of their trend, avoiding a subjective significance measure (Cheng and AghaKouchak [2014\)](#page-7-0). In this study, the non-stationarity is applied to annual maximum rainfall series of all duration (i.e. 1-, 2-, 3-, 6-, 12-, 24- and 48-h) and compared with stationary models of each duration.

The rainfall IDF relationship for 2, 5 and 10 year return period are developed based on the non-stationary GEV models. The IDF curves of Hyderabad city for 2, 5 and 10 year return periods are shown in Fig. 2a–c, respectively. In this study, it is observed that the IDF curves derived from the stationary models are underestimating the extreme events. If such an IDF curve (developed from the stationary model) is used for an infrastructure design, the project may not be able to withstand the very extreme events.

For example, for an event with a return period of 2 years and duration of 2-h, the difference between the non-stationary (35.74 mm/h) and stationary (26.73 mm/h) extreme rainfall is about 8.98 mm/h. Even for a small watershed, this extra 8.98 mm/h rainfall will lead to a significant increase in peak runoff. In addition, for an event with a return period of 5 years and 2-h duration, the non-stationarity and



Fig. 2 Non-stationary intensity-duration curves of Hyderabad city for a 2-year, b 5-year and (10) 10-year return periods

<span id="page-7-0"></span>stationarity extreme rainfall are 41.81 and 32.88 mm/h, respectively. The non-stationary extreme rainfall of 2 year return period (35.74 mm/h) is more than the stationary extreme rainfall of 5 year return period (32.88 mm/h). In other words, the return of period of an extreme rainfall of the Hyderabad city is reducing. In other words, the future extreme rainfall events that exceed the capacity of existing drainage systems may occur more frequently if the drainage is designed based on the concept of stationary extreme value theory.

#### Summary

In this study, with the help of IMD 42 years' hourly rainfall observations, the trend in the Hyderabad city 1-, 2-, 3-, 6-, 12-, 24- and 48-h duration annual maximum rainfall series are analyzed using the Mann–Kendall (M–K) test and a significant increasing trend is observed. Further, based on recent theoretical developments in the extreme value theory (EVT), non-stationary rainfall IDF curve for the Hyderabad city is developed by incorporating linear trend in the location parameter of the generalized extreme value (GEV) distribution. The study results indicate that the IDF curves developed under the stationary assumption are underestimating the precipitation extremes. In other words, the return of period of an extreme rainfall of the Hyderabad city is reducing.

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