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Derivation of new design rainfall in Qatar using L-moment based index frequency approach

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Abstract

For stormwater system design, flood estimation and many other environmental assessment tasks, design rainfall is an essential input. Estimation of design rainfall is generally made using a regionalization technique based on a regional database of observed rainfalls. Many countries have derived their own generalized design rainfall data, which are generally expressed in the form of intensity–duration–frequency (IDF) curves. In Qatar, situated in an arid region, the existing IDF data were developed in 1991 using a limited data set. This paper presents the development of new IDF data for the State of Qatar using the method of L-moments and the index regional frequency analysis approach. The daily rainfall data from 32 stations located in Qatar and nearby Gulf countries have been used to form a homogeneous region. It has been found that the Pearson Type 3 distribution best fits the 24-h duration annual maximum rainfall data in the Qatar region. For the ungauged case, a prediction equation is developed where mean annual maximum rainfall is expressed as a function of climatic and physiographic characteristics. From a leave-one-out validation, it has been found that the developed prediction equation can estimate mean annual maximum rainfall with a median relative error of about 5.5%. Finally, an approximate method is used to obtain design rainfalls for other durations due to the limitations of continuous pluviograph data in Qatar. The new set of IDF curves is based on a much bigger dataset than the existing 1991 IDF curves. It is expected that the new IDF curves will have wider application in Qatar and will provide a statistically sound basis for storm water design, flood and environmental studies. The method can be applied to other middle-eastern states and similar arid countries in the world.

Keywords: IDF; Qatar; Design rainfalls; L-moments; Homogeneous region

1. Introduction

In the planning and design of an urban stormwater drainage system, water infrastructures, flood control measures and various environmental and ecological studies, design rainfall estimates are needed (Madsen et al., 2009). Design rainfall is defined as the rainfall depth associated

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with a given average recurrence of interval (ARI) and duration. Design rainfall is more commonly known as intensity–duration–frequency (IDF) rainfall data. Many countries in the world have derived their own IDF data using a regional data set of rainfall stations over the country. For example, design rainfall in Australia was derived in 1987 (I. E. Aust., 1987), which now has been upgraded in 2013 (Johnson et al., 2012). Similarly, NERC (1975) derived design rainfall data in the UK, Ben-Zvi (2009) for Israel, and Hershfield (1961) and Bonnin et al. (2006) for USA.

To derive IDF data, regional frequency analysis is preferred over the at-site estimation to achieve consistency in estimation over space. Moreover, a regional approach allows estimation of design rainfall at any arbitrary location within the region, in particular at ungauged locations. In the regional frequency analysis approach, recorded rainfall data within a 'homogeneous region' are pooled to compensate the scarcity of temporal data with the spatial data i.e. recorded rainfall data from other stations in the region. In a homogeneous region, it is assumed that all the sites within the region have the same regional growth curve/factors, but the at-site scaling factor (e.g. mean or median value) is unique for each site which reflects the variation of at-site characteristics governing rainfall generation. In many cases, product moment estimation method has been adopted such as the use of Log-Pearson Type 3 (LP3) distribution with product moments for Australia in 1987 (I. E. Aust., 1987). The problem with the product moment estimation is that it suffers more from sampling variability and outliers in the data series.

The homogeneity of a proposed region can be tested by a number of methods. For example, Wiltshire (1986) proposed a method to test the regional homogeneity based on the coefficient of variation (C_v) of the observed hydrological data; however, the test was found to have low power (Fill and Stedinger, 1995). Dalrymple (1960) proposed a homogeneity test based on the sampling distribution of the standardized 10 year annual maximum flow assuming an Extreme Value Type 1 distribution. The regions studied by this method were found to be homogeneous in most of the cases suggesting that the test was not very powerful. Chowdhury et al. (1991) proposed a test based on the L coefficient of variation ($L\ C_v$) and L coefficient of skewness (L skewness) on the assumption of an underlying GEV distribution. The problem with these distribution-specific tests is that when the hypothesis of homogeneity is rejected, it remains doubtful whether the region is heterogeneous or whether it is homogeneous but has some other parent distribution (Hosking and Wallis, 1993).

Since the introduction of L-moment based regional homogeneity testing by Hosking and Wallis (1993), it has been adopted widely in regional rainfall, flood and low flow analyses (e.g. Alila, 1999; Madsen et al., 2002; Hewa et al., 2007; Jakob et al., 2007; Abolverdi and Khalili, 2010; Lee et al., 2010; Sarker et al., 2010; Yang et al., 2010; Haddad et al., 2011; Gabriele and Chiaravalloti, 2012; Zakaria et al., 2012; Pham et al., 2013). The advantages of L-moments are that they are less affected by outliers and extremes in the data (Hosking, 1990) and hence provide more accurate quantile estimates.

The limitation of continuous rainfall data at shorter resolution such as 6 min is a major problem in rainfall estimation. However, in the urban stormwater system design, shorter durations are more important than the longer ones, since urban catchments are relatively smaller (e.g. individual house roof, few lots or smaller sub-divisions). To overcome the limitations of the continuous rainfall data from tipping bucket rain gauges, various degrees of approximations are adopted where daily rainfall data are used to derive 24-h design rainfalls which are then used to estimate shorter duration design rainfalls based on empirical adjustment factors (Al-Layla et al., 1980; Bazaraa and Ahmed, 1991).

The currently recommended IDF data in Qatar were based on the study by Bazaraa and Ahmed (1991). In this analysis, 24-h duration rainfall data recorded at the Doha International Airport for the period 1962–1989 were adopted. A Gumbel distribution was fitted to the 24-h annual maximum rainfall series using the method of moments. To estimate 1-h duration rainfall, an approximate method proposed by Al-Layla et al. (1980) was adopted where the ratios of the 2-year ARI_1 h duration rainfall to T-year ARI_1 h duration rainfall were taken to be 1.35, 1.60, 1.87, 2.10 and 2.32 for $T = 5$, 10, 25, 50 and 100 years, respectively. For 5, 10, 15, 30 and 120 min durations, the ratios (1-h rainfall depth (mm)/D-hour rainfall depth (mm)) based on the USA data were then adopted, which were 0.29, 0.45, 0.57, 0.79 and 1.25, respectively for 5, 10, 15, 30 and 120 min durations.

Since the study by Bazaraa and Ahmed (1991), there are additional rainfall data available in Qatar and surrounding Gulf countries in terms of increased number of sites and data length by about 20 years. Also, there have been notable advancements internationally in the statistical methods for regional frequency analysis, which could enhance the accuracy of the new IDF data for Qatar. Hence, this study presents the development of new IDF data for Qatar using the most up-to-date rainfall data and L-moment based index frequency approach. The main focus of this paper is to identify a homogeneous region for Qatar, select a best fit probability distribution and develop a regional prediction equation to estimate mean annual rainfall as a function of readily available climate and catchment characteristics data so that design rainfall can be estimated at any arbitrary location in Qatar.

2. Study area and data description

This paper uses data from the Qatar region in the Middle East. The climate in Qatar is arid, with rainfall events concentrated in the period October to May. The months June to September are usually completely dry. The monthly average rainfall, based on 49 years of rainfall

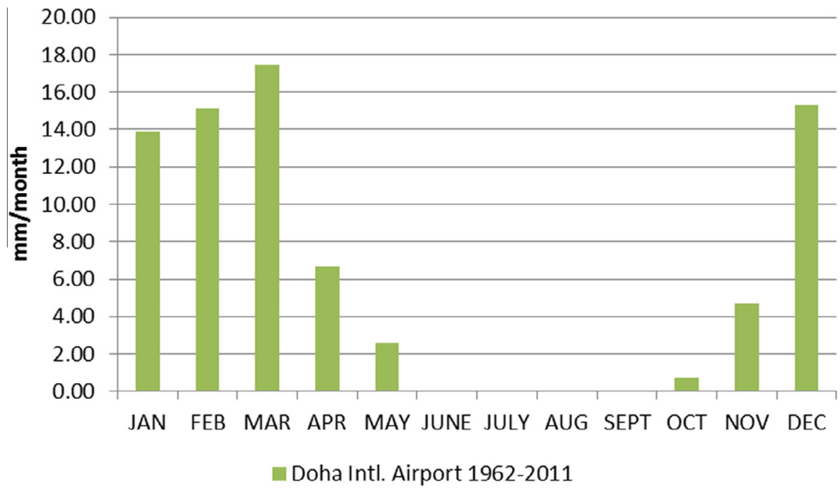

Fig. 1. Average monthly rainfall at Doha International Airport during 1962–2011.

record at the Doha International Airport is shown in Fig. 1. The average annual rainfall measured at the Doha International Airport from 1962 to 2011 is 76.6 mm. The average annual rainfall at nearby airports such as Bahrain International Airport, Manama (1948–2011), is 79.3 mm and at the Sharjah Airport (1949–2011), UAE, is 101.4 mm. The precipitation varies over Qatar with the highest rainfall in the northern part and the lowest in the southern part close to the border with Saudi Arabia.

Rapid urban development has been a major feature in many of the major cities in the Gulf region including Doha, Qatar. This increases the impervious nature of already flat terrain, thereby diminishing the rate of infiltration and increasing runoff from the impervious surfaces. Elevated ground water levels in Doha caused by intensive irrigation and leaking wet utility systems further reduce the soil infiltration capacity. Previously installed soakaways have been found to be inefficient in many instances, which contribute additional runoff during the wet period. It is a common phenomenon to have inadequate urban drainage facility in arid regions like Qatar on the assumption that the rainfall is too low, and hence flooding would not be an issue. However, damages due to flooding caused by intensive storms can be significant even in such arid regions (example shown in Figs. 2 and 3). Ponding of rain water on the roads can cause traffic accidents, sometimes with fatal outcomes. Severe rainfall often causes flood damage to properties in this region. For example, 2009 Jeddah flood, resulting from about 90 mm of rainfall over 4 h, caused 122 deaths and sweeping of over 3000 cars.

For this study, initially a total of 35 sites were selected; however, the finally adopted data set consisted 32 of these sites. The reasons for deleting some of these sites are explained in Section 4. The average record length of the daily rainfall data from these selected 32 stations is 35 years. The distribution of record lengths is shown in Fig. 4, which shows that most of the selected stations have record lengths in the range of 30–40 years. In the data analysis, annual maximum rainfall series was extracted by using

Fig. 2. Flooding of streets during significant storm, Qatar.

Fig. 3. Flooding in Jeddah, Saudi Arabia in Nov 2009 (Wikipedia, 2013).

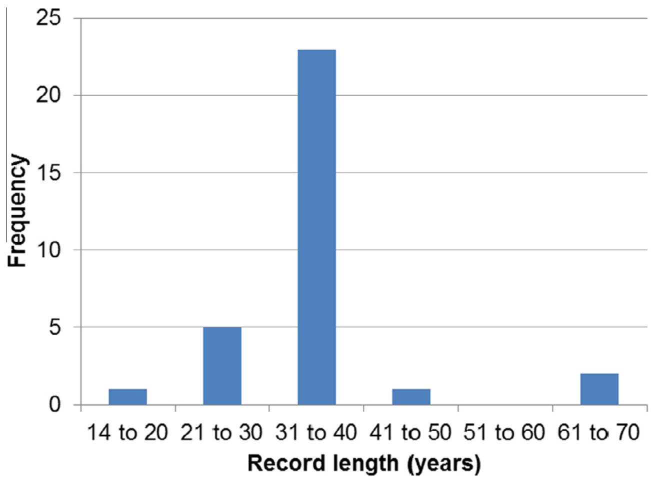

Fig. 4. Histogram of record lengths of daily data of 32 rainfall stations.

a computer program, which identified the maximum rainfall intensity in each year of the available historical data for a 24-h duration at each of the selected sites. A partial duration series could have been adopted, but it may have issues of selection of independent events and hence was not pursued.

Five climatic and catchment characteristics were adopted to develop prediction equation for mean annual rainfall: (i) latitude in degrees (LAT); (ii) longitude in degrees (LON); (iii) shortest distance between the rain gauge and the coastline in km (DCOAST); (iv) shortest distance between the rain gauge and the coastline along the prevailing wind direction in km (DPWD); and (v) free stretch over the sea along the prevailing wind direction in km (DSEA).

3. Methods

An L-moment-based index regional frequency analysis method, introduced by Hosking and Wallis (1993, 1997), has been adopted in this study to develop new IDF data for Qatar.

Hosking (1990) defined L-moments to be linear combinations of the probability-weighted moments (PWMs), introduced by Greenwood et al. (1979). For a random variable X, PWMs may be defined as:

$$M_{p,r,s} = E[X^p(F_X(x))^r(1 - F_X(x))^s] \tag{1}$$

where p, r, and s are real numbers. When $r = s = 0$, Eq. (1) represents the ordinary product moment about the origin of order p. L-moments are defined by:

$$\lambda_r = E[XP^*_{r-1}F_X(x)] \tag{2}$$

where $P_r^*(.)$ is the r-th shifted Legendre polynomial. L-moments can conveniently be expressed in terms of PWMs:

$$\lambda_{r+1} = \sum_{k=0}^{r} p^*_{r,k}\beta_k \tag{3}$$

where $\beta_k = M_{1,k,0}$ and

$$p^*_{r,k} = (-1)^{r-k}\binom{r}{k}\binom{r+k}{k} \tag{4}$$

L-moment ratios, analogous to product moment ratios, are defined as:

$$\tau_r = \frac{\lambda_r}{\lambda_2}, r = 3, 4, \ldots \tag{5}$$

L-moments are more convenient than PWMs in that they are more easily interpretable as measures of distributional shape. For example: λ_1 is the mean of the distribution, a measure of location; λ_2 is the measure of scale; and τ_3 and τ_4 are measures of skewness and kurtosis, respectively. $L\ C_v = \tau = \lambda_2/\lambda_1$ is analogous to the conventional coefficient of variation C_v.

The main advantages of L-moments (over conventional moments) are that L-moments, being linear functions of the data, are subject to less bias, suffer less from the effects of sampling variability, and are more robust than conventional moments to extremes in the data. Conventional moment estimators such as the sample variance and sample coefficient of skewness require squaring and cubing the observations respectively, which cause them to give greater weight to the observations far from the mean; thus, introduce a substantial bias and variance (Hosking, 1990; Stedinger et al., 1992).

The L-moments are defined above for a probability distribution but in practice, these are generally estimated from a finite sample. Given $x_1 \leqslant x_2 \leqslant x_3 \leqslant \ldots \leqslant x_n$ is a finite ordered sample, the unbiased estimator l_r of λ_r is given by:

$$l_{r+1} = \sum_{k=0}^{r} p^*_{r,k} b_k \tag{6}$$

where

$$b_r = \frac{1}{n}\sum_{j=1}^{n} \frac{(j-1)(j-2)\ldots(j-r)}{(n-1)(n-2)\ldots(n-r)} x_j \tag{7}$$

The distributional parameters $\theta_1, \theta_2, \ldots, \theta_p$ are related to $\lambda_1, \tau, \tau_3, \ldots, \tau_p$ and are estimated by the corresponding sample L moments. From many research studies (Potter and Lettenmaier, 1990; Meshgi and Khalili, 2009), it has been found that index flood procedures, coupled with L moments, yield robust and accurate flood quantile estimation.

The L-moment-based index frequency approach can be expressed by the following equation:

$$I_i(T) = \bar{I}_i \times X_T \tag{8}$$

where $I_i(T)$ is T-year rainfall quantile (for a given duration) at site i, $\bar{I}_i$ is site-specific scaling factor e.g. mean annual maximum rainfall (for the given duration). For gauged site, $\bar{I}_i$ is taken as the at-site mean value and for an ungauged site it is estimated from regional prediction equation, expressed in the form of the mean annual rainfall as a function of climatic and physiographic characteristics. Here, X_T

is the regional growth factor, which is the same for all the sites (gauged or ungauged) within the homogeneous region.

The implementation of the L-moment based index frequency approach by Hosking and Wallis (1993, 1997) involves the following five steps: (a) Data screening using a discordant measure (D_i), where a site with $D_i \geqslant 3$ is regarded as discordant. Any site flagged out as discordant needs to be examined for data error and the other physical reason for possible removal from the proposed homogeneous region. (b) Testing for regional homogeneity: The heterogeneity measure (H_i) is calculated based on a Monte Carlo simulation. For $H_1 < 1$, the proposed region is regarded as 'acceptably homogeneous', for $1 \leqslant H_1 < 2$, the region is regarded as 'possibly heterogeneous' and for $H_1 \geqslant 2$, the region is regarded as 'definitely heterogeneous'. (c) Identification of best-fit distribution: This is based on a Z statistic; for a number of candidate distributions, the distribution(s) exhibiting $|Z^{DIST}| \leqslant 1.64$ may be considered to be acceptable. (d) Computation of a regional growth curve, which involves estimation of the weighted average growth curve, which is applicable to any site within the homogeneous region. (e) Quantile estimation: For the gauged site, obtain rainfall quantiles using Eq. (8). For ungauged sites, a regional prediction equation to estimate mean annual maximum rainfall is developed based on gauged sites' data. The most commonly adopted methods to develop such a prediction equation include multiple linear regression based on either the ordinary least squares (OLS) regression (Rahman, 2005) or generalized least squares regression (Stedinger and Tasker, 1985; Haddad and Rahman, 2012). In this paper, we have adopted the OLS regression approach.

To assess the accuracy of the developed regional frequency analysis method, a leave-one-out (LOO) validation method was adopted (Haddad et al., 2013). The LOO test was based on $(n-1)$ sites in each of the n iterations, where n is the number of sites in the adopted homogeneous region. Initially, the first of the n sites in the list was excluded and the regression coefficients were estimated using the $(n-1)$ sites. In the second iteration, the first site was returned back to the database and the second site in the list was excluded and the regression coefficients were estimated using the $(n-1)$ sites. The procedure was repeated until all the sites were excluded one time in the model development phase. In each of these n iterations, the evaluation statistics (Eqs. (9)–(11)) was calculated using each model by applying the model to the site, which was excluded in each step. The LOO, in essence, offers an independent testing of the developed regional frequency model by assuming each of the sites ungauged in each of the iterations.

Three evaluation statistics were used to assess the performance of the developed regional frequency model as described below. The relative error (RE) is computed based on the following equation:

$$\mathrm{RE} = \frac{|y_i - \hat{y}_i|}{y_i} \tag{9}$$

where y_i = observed quantile and $\hat{y}_i$ is the model predicted value. It should be noted that RE is based on absolute differences between the observed and model predicted values. The smaller the RE value, the more accurate the model is.

The Nash–Sutcliffe efficiency (E) is defined as below:

$$E = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{10}$$

where $\bar{y}_i$ is the mean of the observed value. A model with an E value equal to 1 indicates a perfect model.

The relative bias (B_r) is calculated from Eq. (5). The closer the B_r to 0, the smaller the relative bias associated with the model.

$$B_r = 100\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n\bar{y}_i} \tag{11}$$

4. Results

The L-moments were calculated based on annual maximum series for 24-h duration. Three candidate regions were formed as shown in Table 1. Region 1 consisted of 35 sites, which resulted in a 'possibly heterogeneous region' as $H_1 > 1$. Three sites with high discordancy values were excluded from Region 1 to form Region 2. The H value for Region 2 was found to be smaller than 1.00 and hence was considered to be 'acceptably homogeneous'. Thereafter, the rain gauge in Sharjah UAE, which was located far away from Qatar, was excluded to form Region 3, which resulted in a slight improvement in H values. Finally, Region 2 with 32 sites was taken as the final homogeneous region, which contained 63 more data points than Region 3.

The summary of goodness-of-fit test is provided in Table 2. The L-moment ratio diagram is provided in Fig. 5. Two distributions exhibited $|Z^{DIST}| \leqslant 1.64$, which are Generalized Normal and Pearson Type 3 (PE3). Since Generalized Normal distribution is rarely used in rainfall and flood frequency analyses (Haddad and Rahman, 2011), PE3 was adopted in this study as the regional probability distribution to develop the regional growth curve. Fig. 5 also supports the selection of PE3 distribution.

To estimate rainfall quantiles (for 24-h duration and different ARIs) for the 32 gauged sites, Eq. (1) was adopted where mean annual maximum rainfall for 24-h duration of the respective site was used and the derived regional growth factors were based on PE3 distribution.

For the ungauged site application, mean annual maximum rainfall for 24-h duration needs to be estimated from the regional prediction equation, which was developed using a multiple linear regression technique using OLS estimator. The derived model is provided by Eq. (12). The equation was subjected to LOO validation, which provided a coefficient of determination (R^2) value of 76% (median value), median relative error value of 5.48% (Eq. (2)), relative bias value of 0.83 (Eq. (4)) and Nash–Sutcliffe

Table 1
Summary of homogeneity test results.

Region	Number of sites	H_1	H_2	H_3	No. of discordant sites
Region 1	35 (1215 data points)	1.76	0.99	0.91	3
Region 2	32 (1185 data points)	0.95	0.57	0.46	0
Region 3	31 (1122 data points)	0.951	0.45	0.06	0

Table 2
Summary of goodness-of-fit test.

Distribution	$\lvert Z^{DIST} \rvert$	Acceptable
Generalized logistic	4.96	No
Generalized extreme value	1.98	No
Generalized normal	1.10	Yes
Pearson Type 3	0.61	Yes
Generalized Pareto	4.98	No

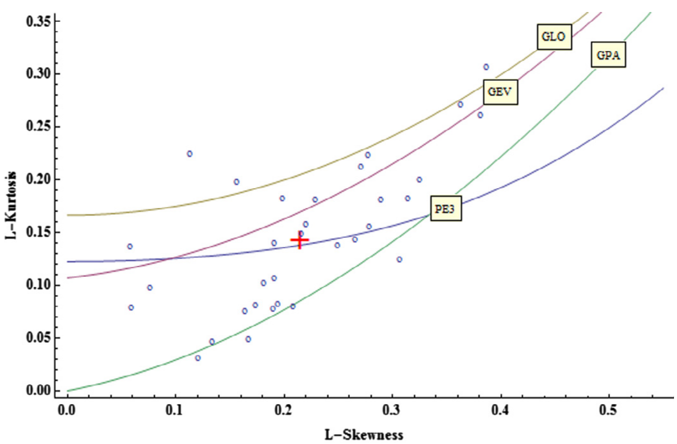

Fig. 5. L-moment ratio diagram for candidate probability distributions.

efficiency of 0.60 (Eq. (3)). The plot of standardized residual and standardized predicted values did not reveal any non-linearity or pattern in the residuals (see Fig. 6 for example). A hypothesis test (at 10% significance level) showed that the null hypothesis that the residuals being normally distributed could not be rejected. These results indicated that the developed regression model satisfied the least squares model assumption satisfactorily and thus confidence can be placed on the equation.

Table 3
Average rainfall depth ratios for Doha and Seeb Airport compared with WMO and IMD ratios.

Time (min)	10	60	120	180	360	720	1440
Doha Airport	0.18	0.40	0.51	0.58	0.71	0.90	1.00
Seeb Airport	0.26	0.56	0.70	0.77	0.87	1.00	1.00
WMO	0.20	0.44	0.54	0.59	0.74	0.84	1.00
IMD	0.19	0.35	0.44	0.50	0.63	0.79	1.00

$$\begin{aligned}\bar{I}_i = {} & -129.573 + 0.955(\mathrm{LAT}) + 2.506(\mathrm{LON}) \\ & + 0.120(\mathrm{DCOAST}) - 0.034(\mathrm{DPWD}) \\ & + 0.005(\mathrm{DSEA}) \end{aligned} \tag{12}$$

The rainfall depth ratios provided by World Meteorological Organization (WMO) and Indian Meteorological Organization (IMD) were compared with the rainfall depth ratios derived from the observed data from the Seeb (Oman) and Doha Airports (Qatar). The results are shown in Table 3. The 10-min value for the Doha International Airport was estimated based on the 10-min rainfall depth ratio given for Seeb Airport and the ratio between the 1-h rainfall depth ratio of the Doha Airport and the Seeb Airport as expressed by Eq. (13).

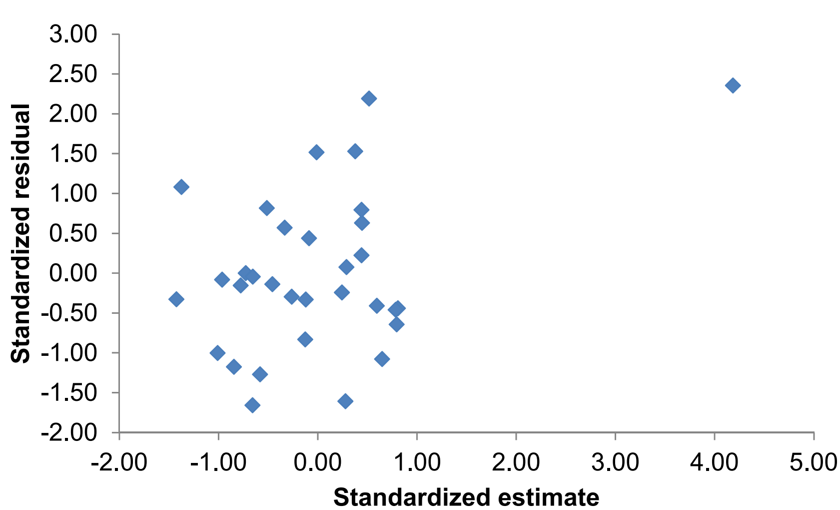

Fig. 6. Standardized residual vs. predicted values for mean annual maximum 24-h duration rainfall model.

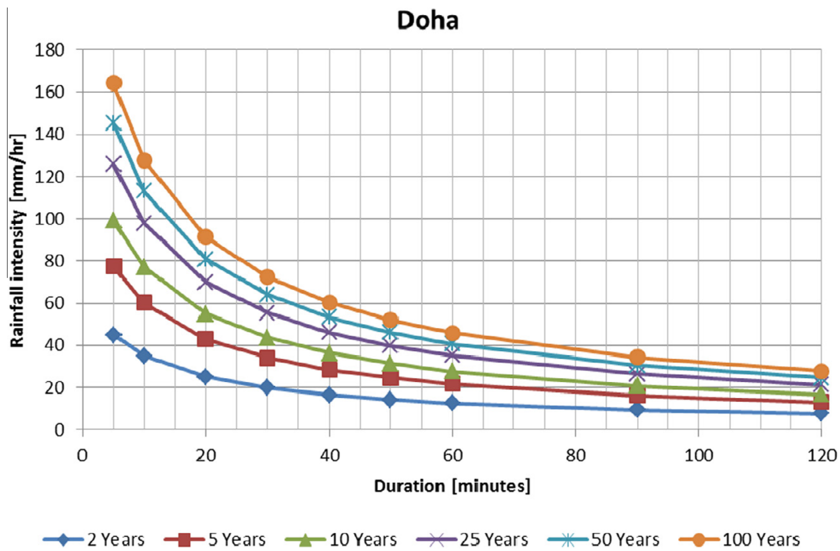

Fig. 7. Final set of derived IDF curves at Doha International Airport.

$$\frac{P_{10\,\mathrm{min}}}{P_{24\,\mathrm{h}}}_{Doha} = \left(\frac{P_{1\,\mathrm{h}}}{P_{24\,\mathrm{h}Doha}} \Big/ \frac{P_{1\,\mathrm{h}}}{P_{24\,\mathrm{h}Seeb}}\right)\frac{P_{10\,\mathrm{min}}}{P_{24\,\mathrm{h}}}_{Seeb} \tag{13}$$

To correct for the restricted duration (for 24-h duration), as per Dwyer and Reed (1995), a correction factor of 1.16 was adopted to convert 24-h restricted to 24-h unrestricted rainfall quantile. To derive the complete set of IDF curves, an approximate method based on the Kimijima method (Eq. (14)) was adopted, in that the finally adopted relationship was expressed by Eq. (15).

$$i = \frac{a}{(t^e + b)} \tag{14}$$

$$i(T,t) = \bar{I}_{24\,\mathrm{h}} \times \alpha_D \times 24\left[\frac{11.182\ln(T) + 11.267}{t^{0.8477} + 7.0636}\right] \tag{15}$$

where $\bar{I}_{24\,\mathrm{h}}$ is the 24-h annual average maximum rainfall intensity at the site of interest (mm/h), $i(T, t)$ is the rainfall intensity (mm/h) for ARI of T-year and duration of t-minute and α_D is the discretization adjustment factor. An example IDF curve for the Doha International Airport is shown in Fig. 7, which represents a consistent set of IDF curves.

5. Conclusions

This study presents derivation of new IDF curves for Qatar using data from 32 rainfall stations. The adopted basic data set consisted of 24-h duration annual maximum rainfall series. An L-moment based index method was adopted to develop the regional growth factors. The proposed region was found to be acceptably homogeneous as the H values were found to be smaller than 1. The best-fit distribution was found to be Pearson Type 3. For an ungauged site application, a prediction equation was developed where mean annual maximum rainfall was expressed as a function of climatic and physiographic characteristics. From a leave-one-out (LOO) validation, it was found that the developed prediction equation could estimate mean annual maximum rainfall intensity with a median relative error of 5.5%. Finally, an approximate method was adopted to derive the design rainfalls for other durations. The new set of IDF curves for Qatar is based on a much larger dataset than the existing 1991 IDF curves. It is expected that the new IDF curves will have wider applications in Qatar. The method can easily be extended to other countries in the region and other similar arid countries in the world.

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