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NON-STATIONARY ANALYSIS OF EXTREME RAINFALL IN PENINSULAR MALAYSIA

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Abstract: Mean and variability of annual and seasonal rainfall in Malaysia are changing due to climate change. The estimation of the return period of extreme rainfall events based on stationary assumption may therefore not be valid in the context of climate change. Estimation of return period of extreme rainfall events for Peninsular Malaysia considering the concept of non-stationary is urgent for the mitigation of flood impacts and adaptation to climate change. This study estimated non-stationary return periods of extreme rainfall events in different locations of peninsular Malaysia using hourly rainfall data. Augmented Dickey-Fuller test assessed the stationary in time series. The extreme rainfall time series were fitted using generalized extreme value distribution and the fitted distribution parameters were estimated using maximum likelihood estimator. The results of 1-, 2-, 3-, 10-, 12-, 24-, 48- and 72-hour at 2-, 10-, 25-, 50-, 100-year return periods at most of the stations showed an increase in maximum rainfall amounts. The highest significant increase was found in Kelantan at 7.62 mm/year for the 72-hour extreme rainfall amount. The maps of the spatial distribution of the non-stationary rainfall amount for different return periods can be helpful for a better design of the hydraulic structure.

Keywords: Non-stationary analysis, hydrological disasters, monsoon, weather management, South China Sea

Introduction

Being a tropical country, the hydrological systems in Malaysia are very sensitive to the changes in rainfall pattern (Tukimat *et al.*, 2012). It was reported that the rainfall amount and intensity have increased over Malaysia due to climate change (Pour *et al.*, 2014; Razaq *et al.*, 2016; Wong *et al.*, 2016; Sa'adi *et al.*, 2017a; Nashwan *et al.*, 2018a). The small increase in the rainfall magnitude and frequency can lead to frequent extreme rainfall events. This is already evident in Peninsular Malaysia from the recent episodes of floods (Deni *et al.*, 2010; Salarpour *et al.*, 2013; Shiru *et al.*, 2018; Wong *et al.*, 2018; Nashwan & Shahid 2018; Nashwan *et al.*, 2018c). Several studies have suggested that floods had severe effects on agricultural activities, infrastructures and property values in Malaysia (Shahid *et al.*, 2015; Ahmed *et al.* 2017; Shahid *et al.* 2017; Tukimat *et al*., 2017). Mitigation of floods through the construction of hydraulic structures like dams, stormwater drainage networks, etc. is therefore very important. For sustainable designing of hydraulic structures, it is very important to assess the changes in maximum rainfall values of different return periods (Tryhorn & DeGaetano 2011; Yilmaz & Perera, 2014).

The rainfall time series can be categorized as stationary and non-stationary based on the amount of variability in rainfall over time. If the means and variances of rainfall do not change significantly over time, the time series is considered stationary. The non-stationary in time series occurs when there is a trend or uneven cycle which eventually change the means or variances of rainfall over time (Noor *et al.*, 2018). The return period of extreme rainfall events is generally estimated based on the historical observed time series data. It is usually estimated with an assumption that the maximum probability of occurrence will not change significantly with time. Inother words, it is assumed as temporarily stationary. This is also followed for estimation of return periods of different intensities of rainfall for designing hydraulic structures in Malaysia. In the Urban Stormwater Management Manual for Malaysia (MSMA) version 2 (DID 2012), the return periods of different storm intensity were estimated using historical observed data with an assumption that the probability of occurrences of rainfall events will not change with time. However, the theoretical distribution of rainfall events based on historical observations will be different for future conditions due to climate change (Noor *et al.*, 2018). Therefore, the assumption of stationary of the statistical properties of rainfall events will not be valid which have made some hydrologists declare that "stationary is dead" (Milly *et al.*, 2008). Others suggested that the consideration of non-stationary process is required to estimate rainfall related extremes such as flood return period (Cohn & Lins 2005; Hirsch & Ryberg 2012), where the parameters of the underlying distribution function are time-dependent and the properties of the distribution will differ over time. Therefore, the return period of different storm intensities estimated in MSMA, based on the assumption of no change in the probability of occurrences of rainfall events with time, will not be valid for future conditions due to climate change. It is very important to estimate the return periods of storm events considering non-stationary in rainfall due to climate. It is expected that estimation of non-stationary return period of extreme rainfall events would help in building climate resilience hydraulic structures for better mitigation planning.

Several approaches have been proposed to incorporate non-stationary in return periods (Park *et al.*, 2011; Obeysekera & Park, 2012; Obeysekera *et al.* 2012; Cooley 2013; Salas & Obeysekera, 2013). Many studies assessed the trends in annual rainfall and rainfall extreme in Malaysia (Pour *et al.* 2014; Mayowa *et al.*, 2015; Sa'adi *et al.* 2017b, Nashwan *et al.*, 2018b). However, studies aimed at assessing the non-stationary in extreme rainfall in Malaysia are very limited. The approaches proposed to incorporate non-stationary in return periods can be classified into four broad classes (Salas & Obeysekera, 2013) namely, (1) probability distribution models embedded with trend components, (2) stochastic models considering shifting patterns, (3) models considering covariates, and (4) probability distributions with mixed components. A number of studies have been carried out based on the above approaches to estimate non-stationary return period in different parts of the world. Sveinsson *et al.* (2005) used stochastic models when considering shifting patterns of parameters like mean and variance. Villarini *et al.* (2010) employed the model considering covariates. Waylen and Caviedes (1986) applied the method of probability distributions with mixed components. Machado *et al.* (2015) used the method of adjusting the non-stationary peak discharges.

Generalized extreme-value (GEV) distribution is a three-parameter model that integrates Gumbel, Fréchet, and Weibull maxima extreme value distribution into a single form. It is recommended in many extreme hydrological applications such as in-situ flood or rainfall frequency analysis (Martins & Stedinger, 2000). The GEV was widely used (Chowdhury *et al.* 1991; Hundecha *et al.* 2008; Cannon 2010; Arreyndip & Joseph, 2016; Cheng *et al.*, 2014) because of its inverse as it had a closed form and parameter can be estimated with ease (Hosking, 1990; Coles *et al.* 2001).

The major aim of this study is to assess the non-stationary behaviour of extreme rainfall events in Peninsular Malaysia. Augmented Dickey-Fuller (ADF) test was used to evaluate the stationary in the annual maximum of 1-hour to 72-hour rainfall events for the period 1970-2014. These extreme rainfall time series were fitted using GEV distributions which were used to estimate their parameters using the Maximum Likelihood Estimator (MLE). Finally, maps were generated to show the estimated non-stationary increment values of different extreme rainfall events. Most of the relevant studies in literature employed daily data in their analysis, but this study used hourly rainfall data as most of the urban flash flooding is usually caused by the extreme amount of rainfall for a short period of time (Shahid *et al.*, 2017).

Methodology

Study Area and Data

Peninsular Malaysia (latitude 1° to 7° N and longitude 100° to 104° E), located in Southeast Asia occupies an area of 130,590 km^2 (Figure 1). It is bordered by the South China Sea to the east, the Strait of Malacca to the west, Thailand to the north and Singapore to the south. As shown in Figure 1, it is divided into 11 states and two federal territories. The topography of Peninsular Malaysia varies from zero to 2,187 m. Peninsular Malaysia has an equatorial climate which can be divided into four seasons dominated by two monsoons, the northeast monsoon (November-March) and the south-west monsoon (May-September) which are separated by two relatively dry seasons (Ismail *et al.*, 2017). The annual rainfall in Peninsular Malaysia varies between 1450 mm and 2575 mm (Katimon *et al.*, 2017; Nashwan *et al.*, 2018c).

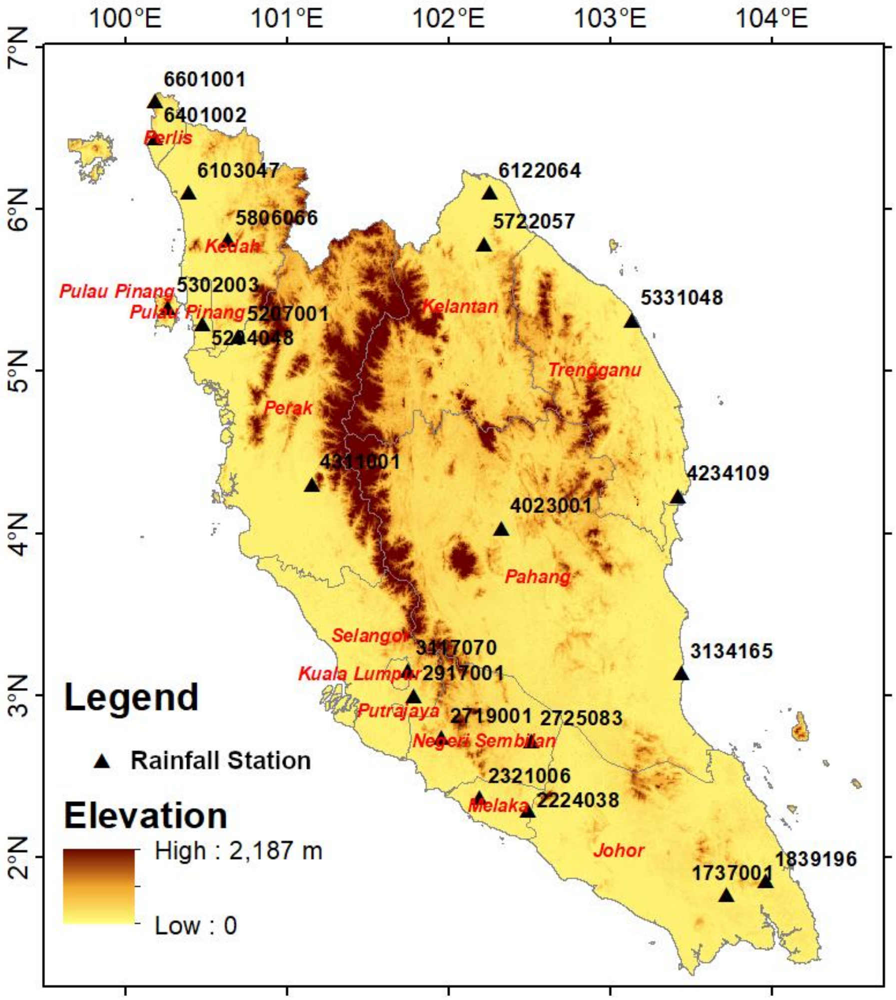

Figure 1: Peninsular Malaysia: Topography, states, federal territories, and locations of rainfall stations

Hourly observed rainfall time series data at twenty-two stations distributed over Peninsular Malaysia were collected from the Malaysian Irrigation and Drainage Department (DID). The DID has a large number of rainfall observation stations in Peninsular Malaysia. However, missing data is the major challenge when using DID's rainfall records for hydrological studies. Rainfall data of twenty-two stations, with a minimum amount of missing data, was used in this study. The time spans of the records without any missing data during the northeast monsoon peak rainfall season were identified for different stations and finally used for analysis in the present study. Therefore, data for different time spans for different stations were used. As the probability based analyses of rainfall extremes were conducted in the present study, it is expected that the use of different time spans of data would not change the outcomes.

Table 1 lists the stations used, their locations and their time spans.

Table 1: List of stations used, their locations and temporal spans of the record

Station ID	State	Latitude	Longitude	Record Span
1737001	Johor	1.7639	103.7194	1974-2014
1839196	Johor	1.8500	103.9653	1970-2014
2224038	Melaka	2.2889	102.4917	1970-2014
2321006	Melaka	2.3639	102.1931	1974-2014
2719001	Negeri Sembilan	2.7375	101.9556	1970-2014
2725083	Negeri Sembilan	2.7194	102.5125	1970-2014
2917001	Selangor	2.9961	101.7858	1975-2014
3117070	Selangor	3.1531	101.7489	1970-2013
3134165	Pahang	3.1375	103.4417	1970-2012
4023001	Pahang	4.0319	102.3250	1973-2014
4234109	Terengganu	4.2319	103.4222	1970-2014
4311001	Perak	4.3056	101.1556	1974-2014
5204048	Penang	5.2939	100.4806	1988-2014
5207001	Perak	5.2167	100.7014	1975-2014
5302003	Penang	5.3958	100.2653	1975-2014
5331048	Terengganu	5.3181	103.1333	1970-2014
5722057	Kelantan	5.7875	102.2194	1970-2014
5806066	Kedah	5.8139	100.6319	1970-2014
6103047	Kedah	6.1056	100.3917	1970-2014
6122064	Kelantan	6.1083	102.2569	1970-2014
6401002	Perlis	6.4458	100.1875	1974-2014
6601001	Perlis	6.6711	100.1869	2001-2014

Several inspections were executed to ensure the quality of the collected hourly data before further analysis for non-stationary as bad quality data may show non-stationary in time series (Salman *et al.,* 2017; Ahmed *et al.* 2018). Of these inspections, a check was carried out on the hourly rainfall higher than 100 mm, no rainfall for longer than a month during the monsoons, among others. The hourly rainfall threshold was taken based on the fact that maximum 1-hr rainfall in the Peninsular never exceeded 100 mm in the period between 1975-2010 (Syafrina *et al.,* 2015). Sequential student's t-test was used to assess the difference between different subsets of time series. A large number of methods are available for assessment of absolute homogeneity in rainfall time series. Among them, the sequential Student's t-test is most widely used (Ahmed *et al.,* 2018). In this parametric test, the null hypothesis of equal mean in two selected sub-samples of a rainfall series is tested. The tests were conducted for all sub-samples of the rainfall series selected sequentially and therefore, it is considered as one of the most sophisticated methods of rainfall homogeneity test (Salman *et al.* 2017, Iqbal *et al.,* 2019). The student's t-test revealed that the difference between collected data was not significant at 95% level of confidence. Furthermore, the histograms of hourly, daily and monthly data were following the typical distribution of hourly, daily and monthly rainfall, respectively, in the Peninsular. Histogram of hourly rainfall at a station located in Johor (Station ID: 1839196) for the period 1970-2014 is presented in

Figure 2. The histogram was prepared using hourly rainfall events having rainfall more than 5 mm. The rainfall of more than 5 mm was used to avoid the large spikes in the histogram for the rainfall events less than 5 mm, as most of the hourly rainfall amounts were in the range of 0.1 to 5 mm, to show clearly the frequency of other rainfall events. The figure shows that hourly rainfall histogram follows the typical pattern which is a sharp decrease in the frequency of high rainfall events. Thus, it was concluded that the collected data was

statistically adequate for this study as there was no significant variation.

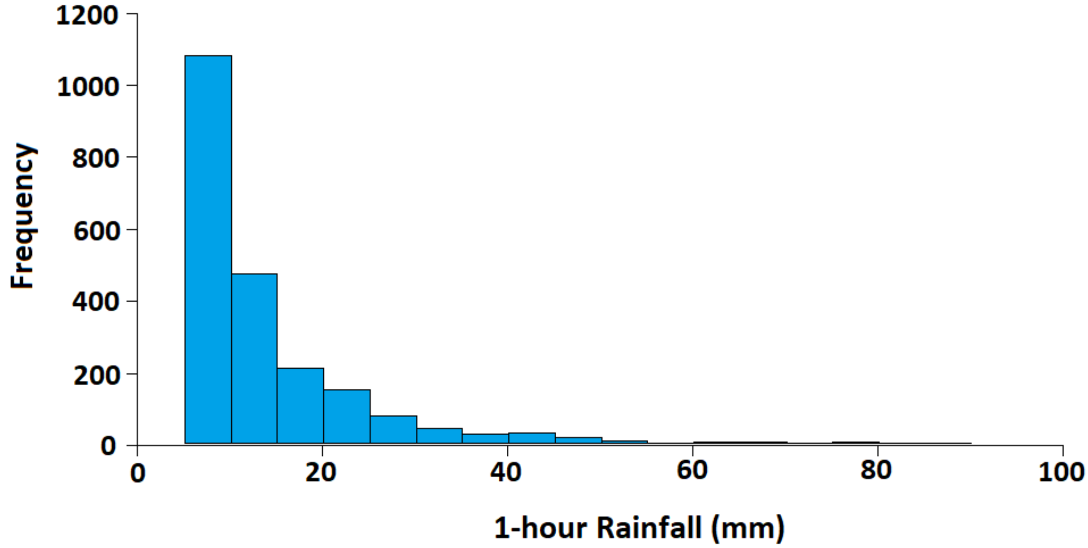

Figure 2: The histogram of hourly rainfall at a station located in Johor (station ID: 1839196) showing a typical pattern of the frequency of rainfall events

Procedure

The procedures adopted to assess non-stationary in return periods of extreme rainfall events in Peninsular Malaysia represented through an info graphic in Figure 3. The general overview of the procedure adopted in the study for the estimation of non-stationary return period of rainfall extremes is as follows. First, the homogeneity of rainfall data was assessed using sequential Student's t-test. The time series of the annual maximum of 1-hour to 72-hour rainfall were generated from hourly rainfall time series for the stations which were found homogeneous. The Augmented Dickey-Fuller test (ADF) was then used to assess the null hypothesis of stationary in all the extreme rainfall time series. Next, the extreme rainfall time series were fitted using different probability distribution function (PDF) and the best fitted distribution function was used to estimate the distribution parameters using Maximum Likelihood Estimator (MLE). The distribution parameters are used to estimate the non-stationary increment values of the return periods of different extreme rainfall events. Finally, maps were prepared to show the spatiotemporal variability in non-stationary increment values of the return periods of different extreme rainfall events. The methods used for the statistical testing of non-stationary using ADF test, distribution fitting, distribution parameter estimation and calculation of the non-stationary return period are discussed in following sections.

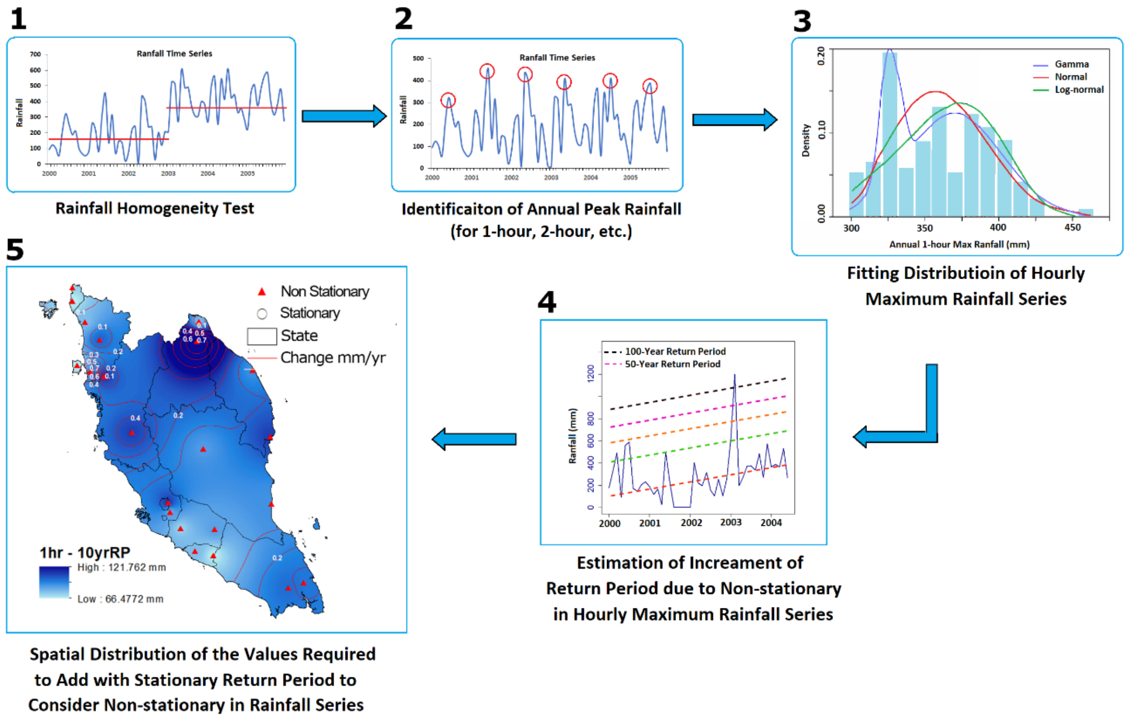

Figure 3: The infographic shows the procedures adopted in the present study to assess the non-stationary in return periods of extreme rainfall events in Peninsular Malaysia

Tests for Stationarity

The Augmented Dickey-Fuller (ADF) test was used for assessing stationarity (Banerjee *et al.* 1993). The null hypothesis of the test is that the time series is stationary, and the alternative hypothesis is that the time series is non-stationary. ADF test was applied at each station to assess stationary in time series at 95% level of confidence using equation (1).

$$\Delta x_n = \alpha + \beta t + \gamma x_{t-1} + \sum_{j=1}^{p}\left(\delta_t \Delta x_{t-j}\right) + e_t \qquad (1)$$

where Δx represents the differenced series at a lag of n years, α represents the drift, β represents the coefficient on a time trend, p is the lag order autoregressive process, γ represents the process root coefficient, δ_t represents the lag operator and e_t is the independent identically distribution residual term with mean zero and variance $\sigma^2 = 0$.

Fitting Probability Distribution Function and Parameter Estimation

The extreme precipitation data were fitted with various Probability Distributions Functions (PDFs). Four PDFs namely, GP, Gumbel, GEV, and Exponential were used to find the best distribution. The GEV distribution was found to best fit the time series at most of the stations in terms of Kolmogorov–Smirnov (KS) test. Therefore, GEV was used for the fitting of extreme rainfall data. The maximum likelihood estimation (MLE) was used for the estimation of distribution parameters. The GEV distribution and MLE parameter estimation methods are described in the following sections.

Generalized Extreme Value

The GEV distribution model integrates the three simple Gumbel, Fréchet, and Weibull's extreme value distributions as in equation (2) (Coles *et al.* 2001):

$$f(x) = \begin{cases} \exp\left(-\left(1 + k\frac{x-\mu}{\sigma}\right)^{-\frac{1}{k}}\right); \mathrm{k} \neq 0 \\ \exp\left(-\exp\left(1 - \frac{x-\mu}{\sigma}\right)\right); \mathrm{k} = 0 \end{cases} \qquad (2)$$

where μ is the location parameter, σ represents the scale and k is the shape parameter. If the distribution is associated with k = 0, the GEV distribution is a

Gumbel such as Pareto, Cauchy, Student-t, and mixture distributions. If k < 0, the distribution is a long-tailed Fréchet which includes Pareto, Cauchy, and mixture distribution. Finally, if the distribution is associated with k > 0, the GEV is a short-tailed Weibull class (Markose & Alentorn 2011). The quantile function represented in equation (3) was used to estimate the return value (Coles *et al.* 2001):

$$f^{-1}(1-p) = \begin{cases} \mu + \left(\frac{\sigma}{k}\right)\{(-\ln(1-p))^{-k} - 1\}; k \neq 0 \\ \mu + \sigma\{-ln(-\ln(1-p))\}; k = 0 \end{cases} \quad (3)$$

where, $f^{-1}(1-p)$ is the quantile function where 0 < p< 1. In the case of k < 0, the GEV distribution has a bounded upper tail, while when k > 0, the distribution shall be heavy tailed (Katz *et al.* 2002). If k = 0, then the distribution has an unbounded thin tail which is a Gumbel distribution. The probability-probability (PP) and quantile-quantile (QQ) plots were used to show the goodness of fitting graphically.

The Maximum Likelihood Estimator (MLE)

The MLE is widely used as one of the dominant parameter estimators (Efron 1982). It is frequently adopted for fitting conceptual models and estimation of PDF parameters. Let a random variable X has the PDF $f(x;\, a_1, a_2, \ldots . a_m)$ with parameters $a_i, i = 1{,}2 \ldots m$, to be evaluated. Drawn from this probability density, a random sample of data $x_i, x_2, \ldots . x_n$, has the joint probability density function represented as:

$$f(x_i, x_2, x_3, \ldots . x_n;\, a_1, a_2, \ldots a_m) = \prod_{i=1}^{n} f(x_i; a_1, a_1, \ldots a_m) \quad (4)$$

The probability to attain a given value of X, i.e. x_1 , is proportional to $f(x; a_1, a_1, \ldots a_m)$. Similarly, the probabilty for attaining the random sample $x_1, x_2, \ldots . x_n$ from the population of X is proportional to the product of the individual probability densities or the joint PDF. This joint PDF is known as the likelihood function and is formulated as:

$$L = \prod_{i=1}^{n} f(x_1; a_1, a_2, \ldots a_m) \quad (5)$$

where, $a_1, i = 1{,}2 \ldots m$, are the unknown parameters. The likelihood of the sample can be determined if n random observations chosen from $f(x; a_1, a_2, \ldots a_m)$ is maximized. The determined values of parameters are termed as the MLE. Since for the same values of $a_1, i = 1{,}2 \ldots, m$, the $\log L$ achieves its maximum as does L, the maximum likelihood formula can also be represented as:

$$\ln L = L^* = \ln \prod_{i=1}^{n} f(x_1; a_1, a_2, \ldots a_m) = \sum_{i=1}^{n} \ln f(x_1; a_1, a_2, \ldots a_m) \quad (6)$$

Non-Stationary in Trends

Like many extreme hydrological events, the extreme rainfall events also show trends over time and thus, the statistical behaviour also changes over time. Therefore, the use of GEV (μ, σ, k) which follows the model for Z_t in time t=1,2,…. has GEV distribution,

$$Z_t \sim GEV(\mu(t), \sigma(t), k(t)) \quad (7)$$

where,

$$\mu(t) = \mu_0 + \mu_1 . t \quad (8)$$

$$\sigma(t) = \exp(\sigma_0 + \sigma_1 . t) \quad (9)$$

$$k(t) = k \quad (10)$$

Hounkpè *et al.* (2015) formulated the effect of the trend with the location parameter of the non-stationary as follows.

$$\mu(t) = \mu_0 + \mu_1 \cdot t \quad (11)$$

Results and Discussion

ADF Test

Table 2 shows the results of the ADF test on the extreme rainfall events. The time series found non-stationary on the ADF test and are indicated by the symbol * in Table 2. Several extreme rainfall events were estimated as non-stationary at most of the stations. All the extreme rainfall events at Stations 5722057 and 6122064 in Kelantan and 6601001 in Perlis, located at the far north of Peninsular Malaysia showed non-stationary behaviour, while most of the extreme rainfall events at Stations 1737001 and 1839196 of Johor and station 3134165 of Pahang showed stationary behaviour.

Table 2: Extreme rainfall events showing non-stationary using ADF test at different stations, indicated by the symbol *

Station ID	**Rainfall Events (hr.)**																		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**10**	**12**	**16**	**20**	**24**	**30**	**36**	**42**	**48**	**60**	**72**
1737001	*	*	*	*	*	*	*												
1839196		*								*	*	*			*	*		*	*
2224038				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
2321006	*		*	*	*	*	*	*	*	*	*		*				*	*	*
2719001	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
2917001	*			*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
3117070	*	*	*								*	*	*	*	*	*	*	*	*
3134165		*	*																
4023001	*	*	*	*			*												
4234109	*	*	*	*	*	*	*	*	*			*	*			*	*	*	*
4311001	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
5204048	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
5207001							*	*	*	*	*	*	*						
5302003	*	*	*	*	*	*	*	*	*	*	*	*			*	*	*	*	*
5331048											*	*							
5722057	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
5806066								*	*	*	*	*	*	*	*	*	*	*	*
6103047	*	*	*	*								*						*	*
6122064	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
6401002	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*			*	*
6601001	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*

Figure 4 represents the ADF test results for the selected stations at the four corners of Peninsular Malaysia. The ADF test results values > 0.05 in Figure 4 indicate a non-stationary behaviour. It can be seen that Station 4234109 located on the east coast of Peninsular Malaysia had higher values, non-stationary, of ADF statistics for the shorter duration of rainfall (e.g. 1, 2, 3, 4 hours) and relatively lower values, stationary, for the longer duration of rainfall (e.g. 36, 48, 60, 72) and vice-versa for Station 2917001 located in the west coast. Station 1737001 located at the southern state of Johor showed a similar trend as the east coast stations, however, with relativity lower values which led to a stationary behaviour for rainfall duration ≥ 8 hours. At Station 5722057, located at the north of the Peninsular, in Kelantan, the ADF test for different extreme rainfall durations showed nearly constant high values with an average of 0.26. Overall, the ADF test indicated non-stationary in most of the extreme rainfall events in the northern states (e.g. Perlis, and Kedah) except for Station 6103047, western states (e.g. Penang, Perak, Selangor, Negeri Sembilan, and Melaka), and eastern states (e.g. Pahang, Terengganu, and Kelantan) expect for Stations 5331048 and 4023001. Meanwhile, stations in the southern state of Johor showed a heterogeneous result indicating non-stationary for some rainfall intensities which depend on the location of the station.

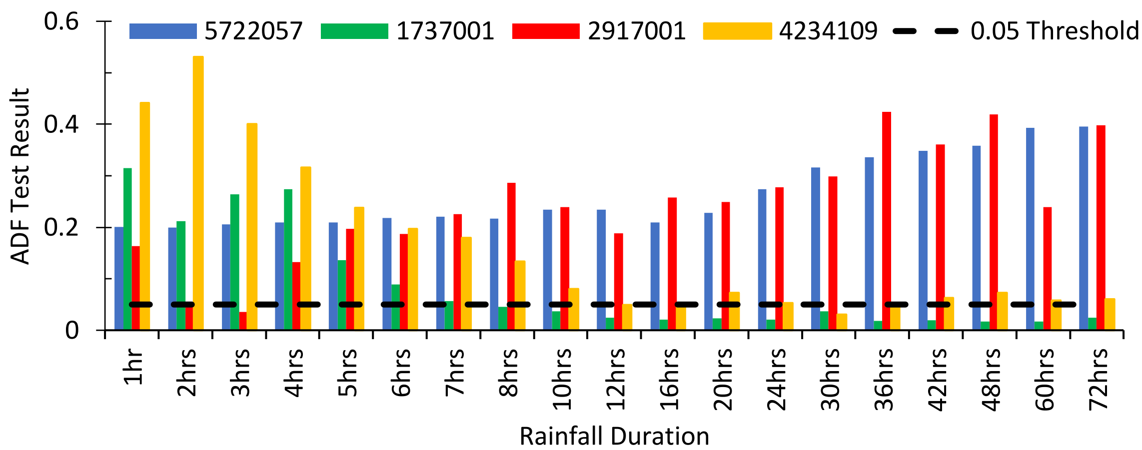

Figure 4: The result of the ADF Test of different extreme rainfall events at selected stations located in four corners of Peninsular Malaysia. The black horizontal dash line shows the 0.05 threshold line

Frequency Distribution Analysis

The quantile plot compares the model quantiles against the empirical (data) quantiles. The quantile plot showing all the points along the diagonal line suggests that the model assumptions may be valid for the plotted data. In this study, most of the data were lined up along the diagonal with some deviations when GEV distribution was considered. As an example, Figure 5 (a) shows the probability and quantile plots for the GEV fit for the 48-hourmaximum rainfall values at Station 5722057 in Kelantan. The figure shows most of the points are aligned along the straight line for both the cases which indicate good fitting of values with GEV distribution with a Root Mean Square Error (RMSE) of 0.86. The PDF plots of modelled and ideal GEV distribution for two stations are presented in Figure 5 (b). The figure shows good matching between the modelledand the ideal distribution which again proves a better fitting obtained using GEV distribution. Therefore, GEV parameters can be used for assessment of non-stationary in rainfall values.

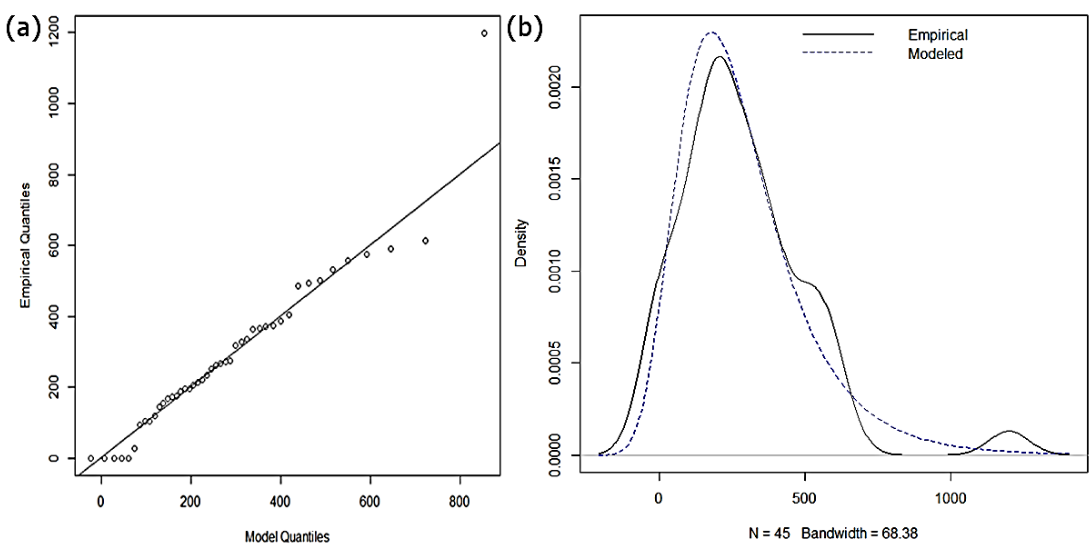

Figure 5: (a) GEV fit diagnostics for 48-hour maximum rainfall amount at station 5722057 and (b) PDF plots of modelled and empirical grev distribution for 48-hour rainfall amount at station 5722057

Figure 6(a) shows the different return periods for the same station, Station 5722057, when the non-stationary behaviour of the extreme rainfall events was not considered. It shows no change in return period values for the same extreme rainfall event (48hours). On the other hand, the extreme rainfall values for different return periods were estimated using equation (7) for the non-stationary case. The 48-hour rainfall values for different return periods at Station 5722057 are shown in Figure 6(b). It clearly shows the non-stationary in return values of the 48-hour rainfall were different atStation5722057. It shows that the 50-year return period value of 48-hour rainfall was 592 mm in 1970 which increased to 821 mm in 2010. Therefore, hydraulic designing using 592 mm as a 50-year return period become completely obsolete.

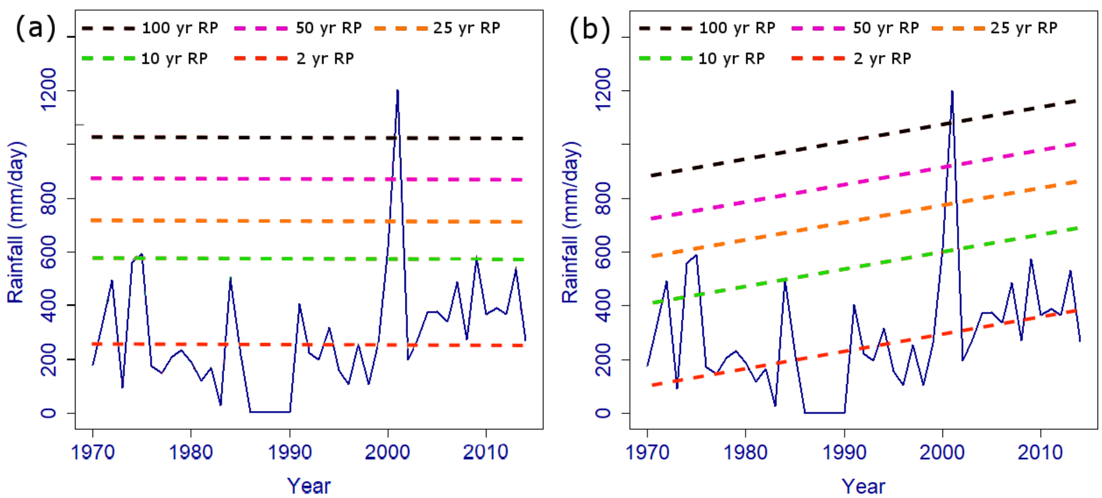

Figure 6: Return periods of the 48-hour maximum rainfall amount when considered (a) stationary and (b) non-stationary at station

The annual increment values of the different extremes and return periods are given in Table 3 where the rate of increase in rainfall values for different return periods can be used for estimation of a realistic return value and designing of hydraulic structures. The shaded red and green represent values ≥ 10th and ≤ 90th percentile, respectively.

The non-stationary increment values of all the return periods of different extreme rainfall events namely, 1-, 2-, 3-, 10-, 12-, 24-, 48- and 72-hour at all the stations of Peninsular Malaysia were estimated and shown in Figure 7. These values were interpolated using the IDW method to prepare a contour map of Figure 7 to show the spatial variability in increment values. The triangles in the map represent the stations found non-stationary while circles represent the stations found stationary for the corresponding rainfall event and return period. The background colour represents the maximum rainfall amount for different durations interpolated using IDW. The maps can be used for the estimation of the changes in rainfall values for different return periods with time. The maps of Figure 7 can be used for reliable estimation of extreme rainfall amounts for different return periods in the context of non-stationary in rainfall due to climate change. All the maps show a higher increase in maximum rainfall amount for different return periods in the northeast of the peninsula. Besides, a significant decrease in the 10-year return period rainfall amount was found in the central part of the peninsula. The 72-hour maximum rainfall events at 10-year return period showed the highest non-stationary increment values, especially in Kelantan. For 3-, 6-, 12- hour maximum rainfall amounts, some of the stations showed stationarybehaviour, especially in Penang and Perak.

Table 3: The non-stationary incremental values of different extreme rainfall events at different stations of Peninsular Malaysia. The red and green shades represent values ≥ 10th and ≤ 90th percentile, respectively.

Station ID	**Rainfall Events (hr.)**																		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**10**	**12**	**16**	**20**	**24**	**30**	**36**	**42**	**48**	**60**	**72**
1737001	0.29	0.13	0.16	0.07	-0.01	0.00	-0.04	-0.10	-0.09	-0.09	-0.16	-0.22	-0.22	-0.36	-0.57	-0.69	-0.78	-0.66	-0.71
1839196	0.35	0.37	0.03	0.45	0.48	0.53	0.57	0.63	0.71	0.77	0.75	0.69	0.68	0.88	0.94	0.94	0.68	0.66	0.72
2224038	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.37	0.50	0.37	0.11	0.08	-0.03	0.02	-0.01	-0.09
2321006	0.06	-0.70	-0.85	-0.96	-1.04	-1.04	-1.06	-1.04	-1.06	0.01	0.01	-0.90	-0.76	0.02	-0.60	-0.77	0.01	0.01	-0.68
2719001	0.04	0.35	0.02	0.02	0.02	0.03	0.06	0.02	0.01	0.06	0.06	-0.16	-0.31	0.01	0.01	0.00	0.00	0.04	0.29
2725083	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2917001	0.04	0.04	0.04	0.04	0.82	0.04	0.78	0.78	0.93	0.91	0.82	0.69	0.56	0.44	0.00	0.43	0.31	0.58	0.60
3117070	0.04	0.22	0.03	0.27	0.03	0.04	0.04	0.37	0.36	0.12	0.20	0.04	0.23	0.03	0.36	0.41	0.03	0.22	0.01
3134165	0.04	0.56	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4023001	0.02	0.02	0.02	0.02	-0.20	-0.23	-0.18	0.00	-0.19	-0.22	0.00	-0.28	-0.29	-0.20	0.00	-0.13	-0.17	-0.01	-0.37
4234109	0.05	-0.01	0.01	0.58	0.63	0.61	0.01	0.50	0.00	0.40	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00
4311001	0.49	0.05	0.04	0.03	0.04	0.21	0.04	0.28	0.03	0.35	0.20	0.18	0.27	0.41	0.01	0.59	0.65	0.61	0.53
5204048	0.89	0.34	-0.03	-0.20	-0.21	0.00	-0.41	-0.42	-0.44	-0.50	-0.72	-0.57	-0.01	-0.27	-0.01	0.09	-0.01	-0.06	0.29
5207001	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5302003	0.31	0.02	0.00	0.10	0.00	0.00	-0.12	-0.15	-0.20	-0.27	-0.35	-0.42	-0.47	-0.54	-0.68	-0.77	-0.75	-0.71	-0.80
5331048	0.04	0.02	0.26	0.30	0.34	0.27	0.26	0.00	0.24	0.14	0.00	0.01	-0.24	-0.41	-0.32	-0.27	-0.35	-0.29	-0.04
5722057	0.78	1.16	1.48	1.89	2.28	2.63	-0.02	-0.02	3.55	4.02	4.44	5.43	5.89	6.15	6.25	6.50	6.70	7.15	7.62
5806066	0.00	-0.01	-0.14	0.00	0.00	0.00	0.01	0.00	0.00	-0.14	-0.10	0.00	0.01	0.00	-0.26	-0.35	-0.45	-0.42	-0.42
6103047	0.14	0.04	-0.06	0.09	0.05	-0.23	0.01	-0.06	0.06	-0.17	-0.12	0.02	0.01	0.01	-0.33	-0.38	-0.35	-0.47	0.00
6122064	0.04	-0.30	-0.22	-0.30	-0.36	-0.40	-0.49	-0.58	-0.67	-0.61	-0.64	-0.46	-0.54	-0.42	-0.25	-0.31	-0.30	-0.01	-0.36
6401002	0.01	-0.33	0.00	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.25	0.57	0.05	0.29	0.03	0.03	0.00	0.00	0.00
6601001	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.03	0.04	0.01	-1.18	-1.37	-0.98	-1.34	-1.30	0.31	-1.69	0.00

For example, the map of 1-hour extreme rainfall for a 10-year return period showed how the extreme rainfall values are changing with time. The higher increase in rainfall values was found in Penang at Station 5204048, located in the northwest of the peninsula (0.86 mm/year). Therefore, for the designing of hydraulic structures concerning 1-hour return period of rainfall, instead of relying on rainfall amount estimated for the historical period, 0.86 mm/year values should be added to the amount of historical mean for every year. None of the stations showed a stationary behaviour for this extreme rainfall event for a 10-year return period. Developing several maps for each return period is recommended as they can be beneficial for robust design of hydrologic structures.

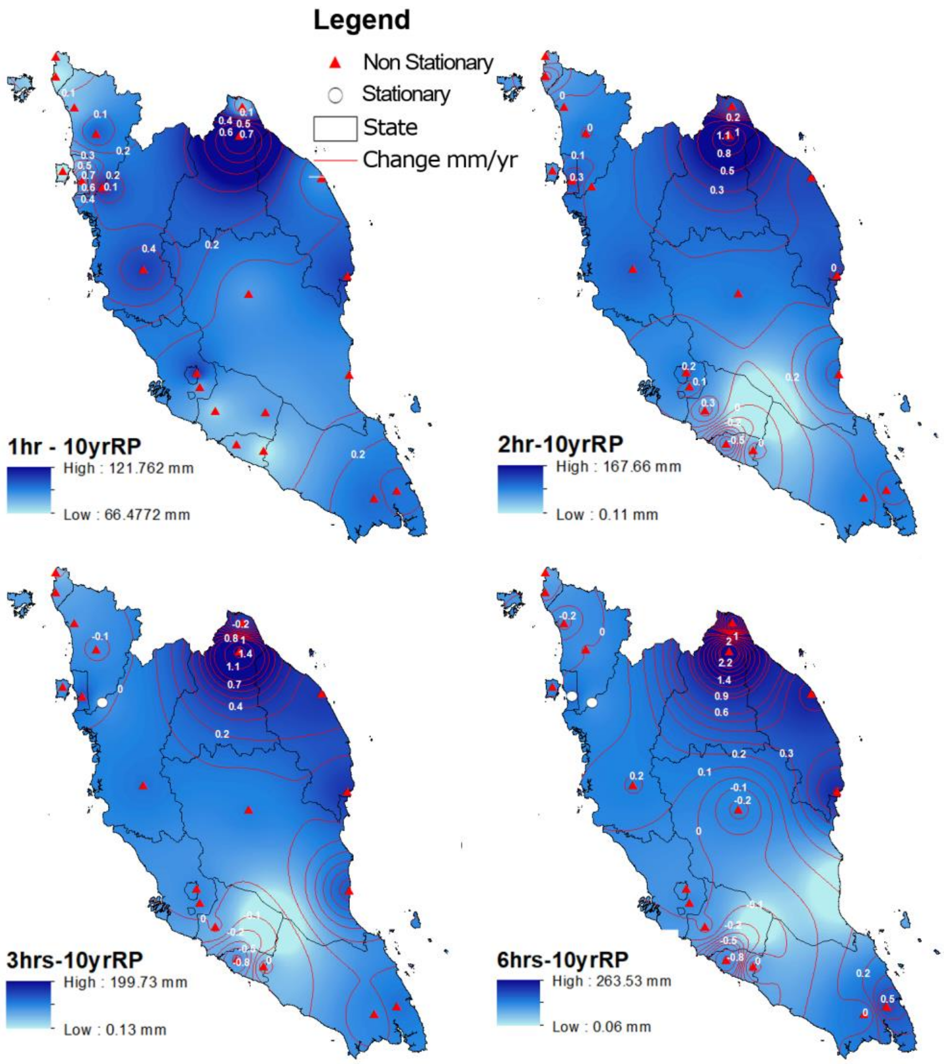

Figure 7: The spatial distribution of different extreme rainfall amounts for a 10-year return period shown using the colour ramp, and the non-stationary increment values shown as contour lines

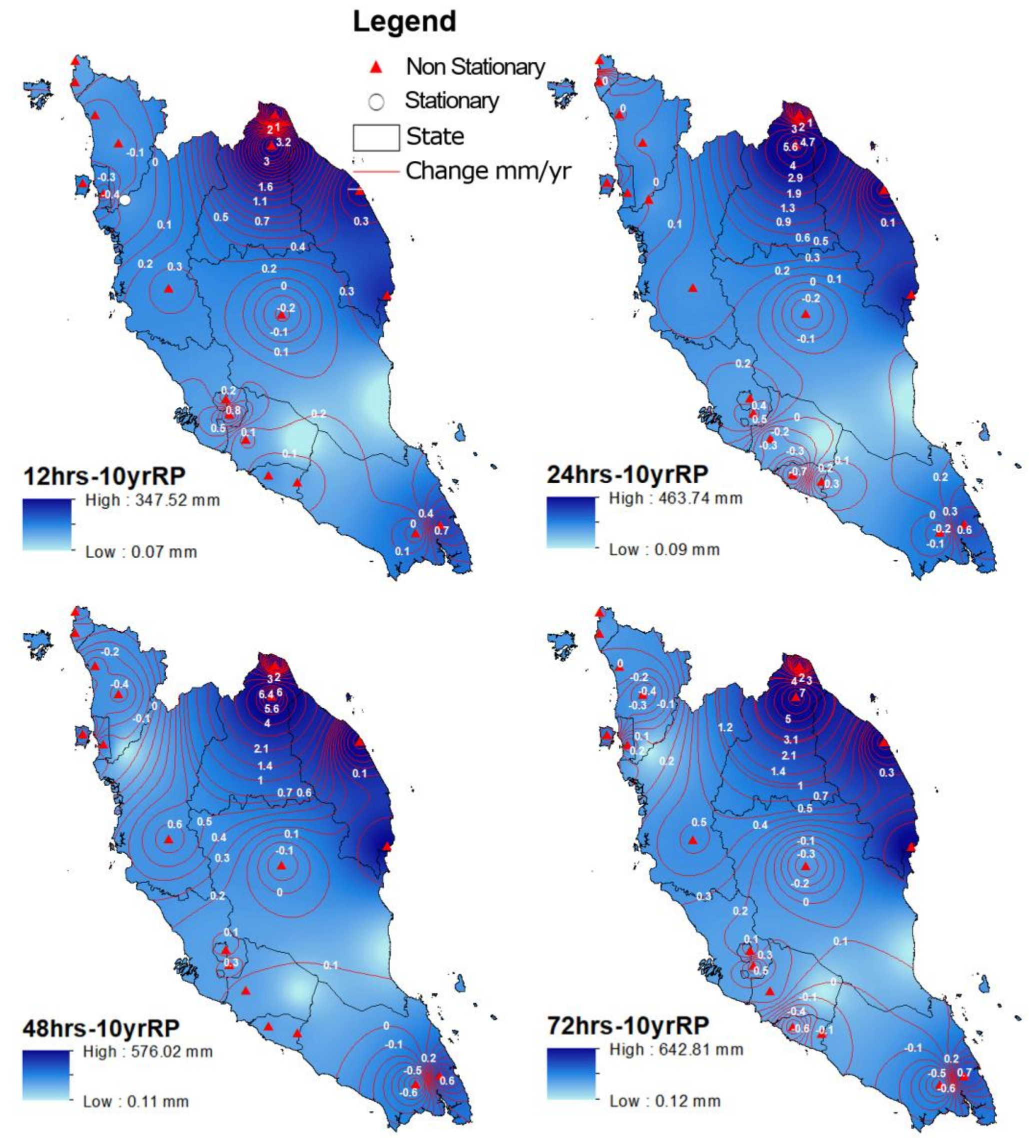

Figure 7: Cont.

Discussion

Climate change has shown a significant effect on rainfall patterns in many regions of the world which will possibly increase in future. Some of the most severe impacts on increased rainfall intensities have been observed in urban cities resulting in huge economic, environmental, infrastructural and human losses. The water management infrastructures should be designed considering future climate changes in order to mitigate the impact of increasing rainfall intensity. However, the development of hydraulic structures, taking into consideration higher intensities of storms due to climate change, will certainly incur more installation cost which is often challenging for developing countries. Identification of location showing non-stationary in rainfall extremes and mapping the non-stationary increment values can be helpful in planning adaptation to climate change in stormwater management cost-effectively.

The non-stationary return periods of extreme rainfall events in different locations of Peninsular Malaysia using hourly rainfall data have been assessed in this study. The extreme precipitation data were fitted with four PDFs namely, GP, Gumbel, GEV, and Exponential. The GEV distribution was found to best fit the time series at most of the stations in terms of KS test. A number of studies have been performed in Malaysia for determining the most suitable probability distribution of extreme rainfall events. Zalina *et al.*(2002) compared eight probability distributions and found GEV as the best fitting distribution to represent the annual maximum rainfall series in Peninsular Malaysia. Noor *et al.* (2018)tested different PDFs for fitting the annual rainfall maxima (1 to 72 hr of rainfall) at 19 locations in Peninsular Malaysia and reported GEV as the most suitable PDF at most of the stations. This indicates the consistency in the results obtained in the present study with the findings of other studies in Peninsular Malaysia.

The study revealed that extreme rainfall events have become non-stationary at various locations of Peninsular Malaysia and the majority of the stations showed non-stationary using ADF test for maximum rainfall amounts of different rainfall durations. No study has been conducted so far in Peninsular Malaysia to assess non-stationary in annual maximum rainfall. Therefore, it was not possible to compare the findings of the present study with others. However, a large number of studies have been conducted in different parts of the world to assess non-stationary in rainfall extremes (Sugahara *et al.*, 2009; Villarini *et al.* 2010; Tramblay *et al.*, 2013). The studies showed that rising temperature has increased evapotranspiration and air moisture holding capacity which have eventually changedthe spatial and seasonal distribution of rainfall in different parts of the world. The changes in mean and variability have caused an increase in the probability of rainfall extremes (Li *et al.* 2018; Nashwan *et al.* 2018a; Nashwan *et al.* 2018c) and thus, made the extreme rainfall events non-stationary. A number of studies reported changes in mean and variability in annual and seasonal rainfalls in Peninsular Malaysia (Wong *et al.*, 2016; Li *et al.*, 2018). It can be anticipated that these changes have caused an increase in frequency and intensity of extreme rainfall events and made their recurrence non-stationary.

Conclusion

The non-stationary in the return periods of hourly extreme rainfall events in Peninsular Malaysia has been assessed in this study. The ADF test was used to assess the stationary in time series. The hourly extreme rainfall time series were fitted using different PDF and the best-fitted PDF was used to estimate the distribution parameters using maximum likelihood estimator. The results revealed non-stationary in maximum rainfall amounts of different rainfall durations at the majority of the stations in Peninsular Malaysia. The percentage of stations showing non-stationary behaviour in extreme rainfall was found to vary for different intensities. The 20-hour rainfall was found to show non-stationary at the highest number of stations (81%) while the 30-hour rainfall at the least number of stations (52%). The higher increase in extreme rainfall amount for different return periods was observed in the north eastern coastal regions. Non-stationary in extreme rainfall should be considered for designing hydraulic structures for adaption and mitigation of negative impacts of climate-induced extreme events. Furthermore, it is suggested that assuming extreme rainfall events as stationary may lead to high uncertainties in the prediction of floods, resulting in an underestimation of flood risk and under sizing the flood retaining and mitigating structures. Therefore, the results presented in this paper can be helpful for adaptation and mitigation of climate change impacts on hydraulic structures in Peninsular Malaysia.

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