ASSESSMENT OF CLIMATE CHANGE IMPACTS ON RAINFALL SERIES IN PENINSULAR MALAYSIA USING STATISTICAL METHODS

By

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ABSTRACT

There is growing interest in quantifying the impact of climate change on extreme hydrologic events where failing to integrate the effect of climate change in rainfall estimation will underestimate the severity of the events and the adequacy of current hydraulic structure designs. The purpose of this study aims is to assess the rainfall trend and frequency analysis with impact from climate change in Peninsular Malaysia using statistical methods.

The thesis consists of two sections, where the statistics of rainfall trend are assessed by Mann-Kendall (MK) test and non-stationary tests while the frequency analysis illustrates the changes in distribution functions that fit full series and sub-series of annual maximum rainfall. The study area is delineated into five regions according to their distance to the nearest coast (the different extents of the influence of monsoon to the study area) to examine the spatial characteristic of the rainfall series.

The MK test has detected changes for each delineated region during different monsoon seasons. At the same time, the result of non-stationary tests reveal that changes in rainfall trend have developed around year 1995 in most of the stations (41% to 50% annual rainfall over the west coast regions; more than 50% of the short duration annual maximum rainfall in the central west region have shown non-stationarity). Among the regions, the short duration rainfall in central west region show most significant increasing trend by both the MK test and the non-stationary tests. Thus, year 1995 served as trend change-point to split full series

data into two sub-series data and frequency analyses are performed on these data sets.

From the outcomes of the frequency analysis using two sub-series data sets, the estimated quantiles from most of the regions have increased when the sub-series posterior to 1995 is used compared to full series data, implying an overall upward rainfall trend. The results also indicate that the combination of Generalised Extreme Value distribution function and L-moments for parameters estimation (GEV-LM) outperforms the other choices. The GEV-LM is able to fit well to all regions for short-duration rainfall and three regions for long-duration rainfall.

This study demonstrates the importance of incorporating climate change in rainfall assessment. There are two-fold implications of this study. First, there is considerable variability of rainfall patterns due to climate change and hence, it is important to divide the study area into regions based on the results of the MK trend and non-stationary tests. Then, the best fitted distribution function and parameter estimation method combination for frequency analysis should be tested for every region. Second, it is important to appreciate the non-stationarity of rainfall series due to climate change and the impact on how frequency analysis shall be carried out.

As the warming trends in Peninsular Malaysia started around year 1995, rainfall series have shown significance upward trend, while the results of the frequency analysis (estimated quantiles) reflects the changes in the rainfall characteristics as well. Hence, in this case, it is important to concern the non-stationarity in data to achieve better estimation performance using frequency analysis.

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CHAPTER 1: INTRODUCTION

Hydrologic statistical methods have been applied to evaluate rainfall and associated flooding events to address concerns in water resources management and hydraulic structure design. Over the past 10 years, Peninsular Malaysia has experienced frequent incidents of severe flooding that could be attributed to climate change. Hence, it is essential to assess the changes of rainfall patterns and its effect on the outcomes of the frequency analysis. Such pattern changes should be quantified and incorporated in design guidelines and standards. In addition, research that incorporates the impact of climate change in frequency analysis study is still rather limited. By neglecting the effects of climate change, rainfall estimation may underestimate the severity of events.

1.1 BACKGROUND

The threat of climate change is an unquestionable concern and should be considered as one of the most critical environmental issues faced in the world today. According to IPCC (2014), both anthropogenic and natural factors are contributing to variations in climate. For example, human activities such as the combustion of fossil fuels change the composition of atmospheric greenhouse gasses and; the modification of land use that consequently alters the energy balance in the climate system. Such activities have been identified as causes of climate change (IPCC, 2014; National Research Council, 2010). On the other hand, natural causes of climate change comprise of internal processes like the El Niño-Southern Oscillation (ENSO) phenomena that occurs on inter-annual time-scales and; external forcing which consists of volcanic eruptions, solar variation as well as the orbital change of the Earth also contribute to climate change (IPCC, 2014; Nicholls, 2007).

According to IPCC (2007), in the twelve years between 1995 and 2006, the world has experienced eleven of the warmest years in the instrumental record of global surface temperature since 1850. As shown in Figure 1.1, the fluctuations of temperature anomalies indicate a more pronounced positive trend beyond year 1995.

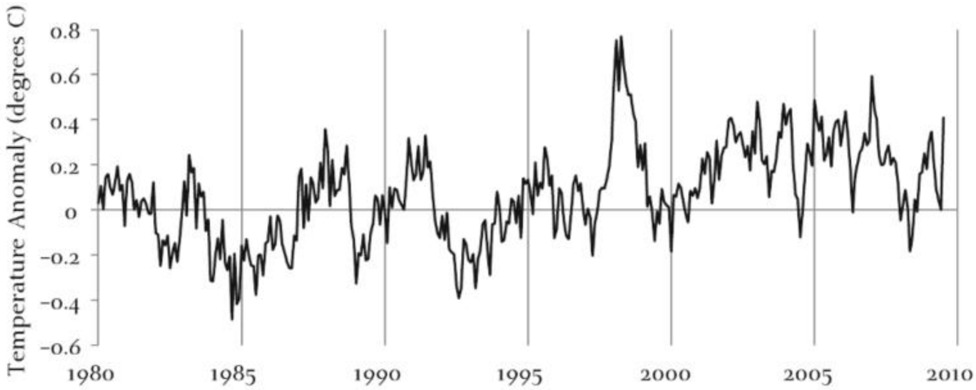

Figure 1.1: Global average temperature variations from 1980 – 2010 (Spencer, 2012)

Climate change is likely to impact the hydrological cycle on a regional as well as global scale (Kuchment, 2004). A study by Nicholls et al. [cited Hulme et al., 1998] showed that the global mean precipitation is expected to increase by 0.5 to 1.8% with a rise in temperature around 0.3 to 0.6˚C. Yamakawa & Suppiah (2009) also found that extreme climatic events (e.g. excessive rainfall events in Japan, heavy snowfall in China and severe drought in Australia) that have occurred in recent years are due to the combination of natural climatic phenomena and long-term global warming.

1.1.1 Climate Change in Malaysia

In the Malaysian context, Malaysia is experiencing warming trends from 1950s to 2000s as shown in Figure 1.2. From the 1990s, the behaviour of ENSO has seemed unusual relative to that of previous decades. A prolonged period of low Southern Oscillation Index (SOI) occurred from 1990–1995, during which several weak to moderate El Niño events occurred with no dominant La Niña events, which is extremely rare in statistical terms (Trenberth & Hoar, 1996). It also has been observed that the persistent warm phase from 1990 to mid-1995 was unusual in the last 120 years and has significantly influenced rainfall in Malaysia (Zhao et al., 2014).

The correlation analysis of regional annual temperature records in different regions in Malaysia indicated warming trends and consistent positive anomalies are mostly detected after year 1995. Figures 1.2 to 1.6 show the maximum temperature anomaly for different regions in Peninsular Malaysia (Malaysian Meteorological Department, 2015).

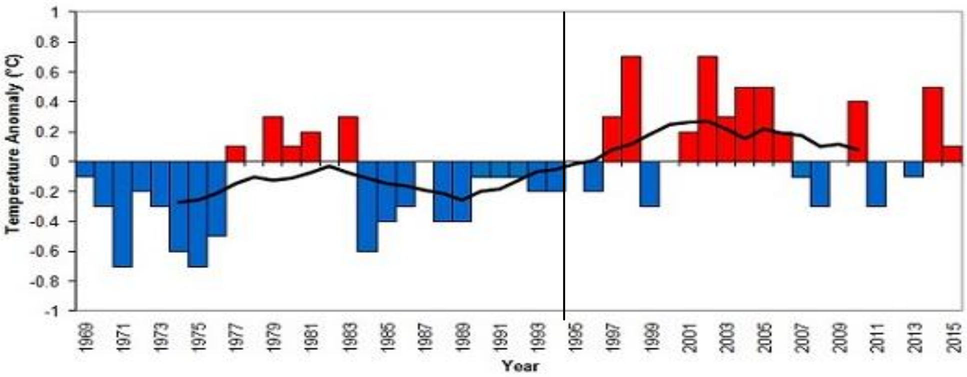

Figure 1.2: North peninsula maximum temperature anomaly

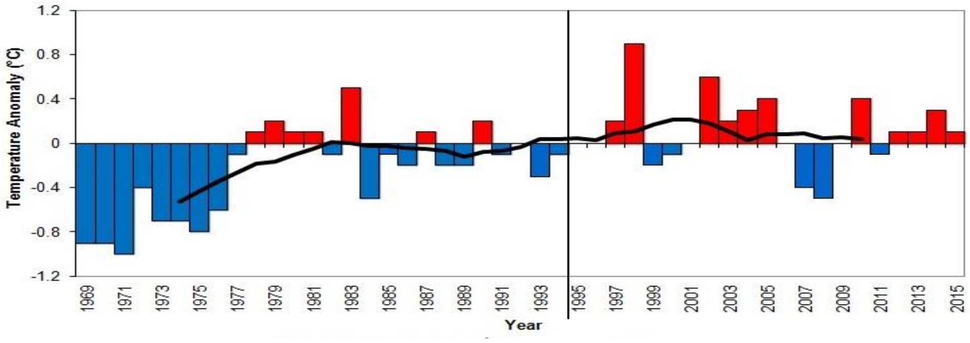

Figure 1.3: Central peninsula maximum temperature anomaly

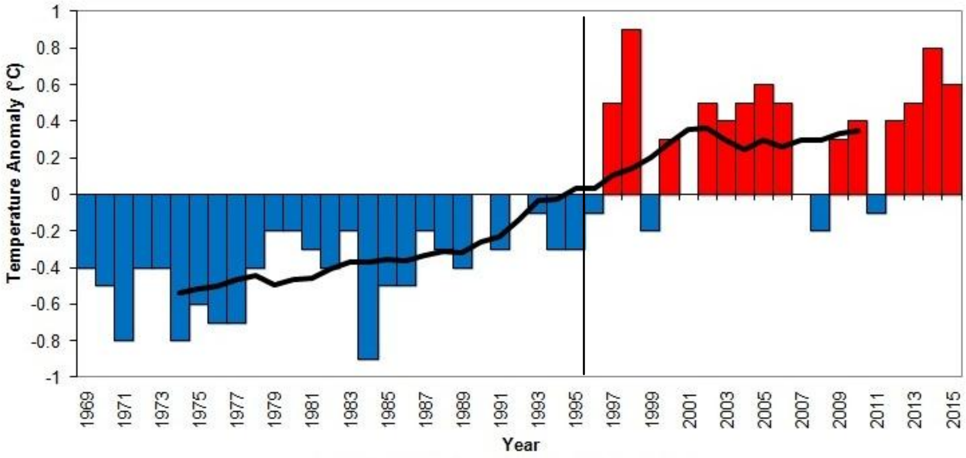

Figure 1.4: South peninsula maximum temperature anomaly

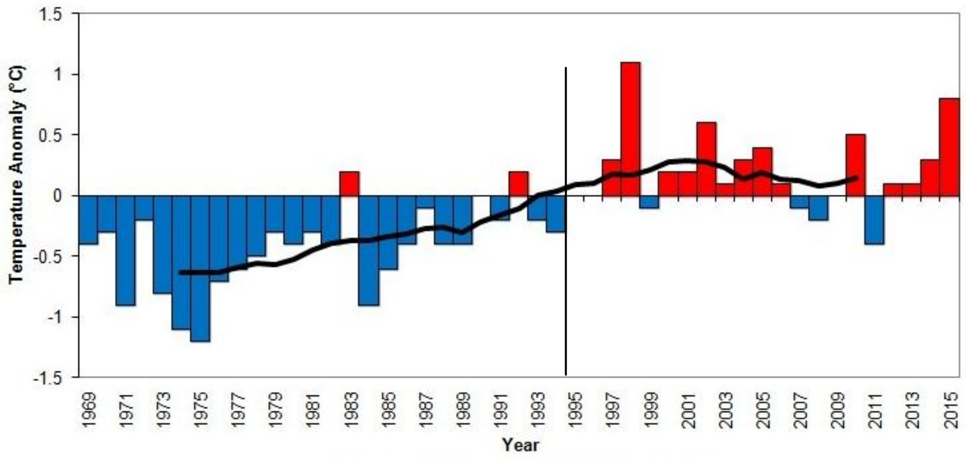

Figure 1.5: East peninsula maximum temperature anomaly

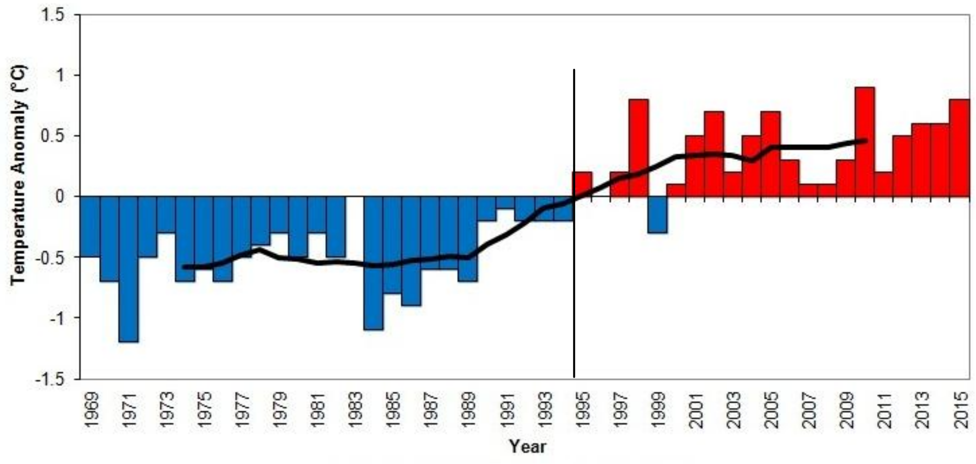

Figure 1.6: Cameron Highland's maximum temperature anomaly

According to temperature data from Malaysian Meteorological Department (2015), the warming trends in Peninsular Malaysia have started around the mid-90's.

1.2 IMPACTS ON RAINFALL AND FLOOD

The increasing frequency and intensity of extreme hydrologic events (Tompkins, 2003) and increases of uncertainty in the climate system that effectively reduced its predictability (Tsonis, 2004) have been considered as anticipated effects of climate change. Furthermore, some aftereffects of climate change impacts have been observed such as the increased occurrence of flooding due to changes in rainfall patterns (Trenberth, 2010; Guhathakurta et al., 2011). This, in turn, has affected agricultural activities in growing seasons based on water availability (Mearns et al., 1997).

According to Rind et al. (1990) and Trenberth (2010), there are higher variations in spatial and temporal patterns of regional precipitation (detected changes in different regions of study area and during different seasons or even inter-annual occurrence events) that have led to the increased occurrence of floods and drought in many regions in the world under the influence of climate change. For instance, Dore (2005) has done an extensive review on the changes in global precipitation patterns and summarized the variations of precipitation pattern: (i) the precipitation in Northern Hemisphere has increased; (ii) reduction of rainfall in several regions such as China, Australia and Small Island States in Pacific; (iii) the changes of rainfall pattern across equatorial regions is highly inconsistent in temporal and spatial patterns.

For Peninsular Malaysia, there is evidence indicating the intensity of rainfall has increased based on the recorded rainfall data from Department of Irrigation and Drainage (DID) Malaysia. The comparison of one-hour, three-hour and six-hour rainfall intensities for the periods 1970-1980 and 2000-2007 in Ampang, Kuala Lumpur has shown increasing trends by 17%, 29% and 31% respectively (Ministry of Natural Resources and Environment Malaysia, 2010). The changes in rainfall trend have also been observed by the people living along the shoreline. In a study carried out on the impacts of global warming (Mohamed Shaffril et al., 2011), most of the interviewees (fishermen) agree that global warming has led to inconsistent rainy seasons and the east coast of Peninsular Malaysia has experienced more frequent rainfall events.

For floods in Peninsular Malaysia, the occurrences of 100-year return period floods have become relatively frequent from year 2003 to 2012, especially in Johor. The frequent occurrence of extreme flood events in Johor has been attributed to the impact of global climate change (Rahman, 2009). Between year 2006 to 2011, Johor has been struck three times (in December 2006, January 2007 and January 2011) by flood with severity of more than 100 years (Atikah, 2009). During the event in December 2006, the maximum

48-hour[1] recorded rainfall was 473 mm at Ulu Sebul, Kota Tinggi; while in January 2007, the maximum 24-hour[2] recorded rainfall was 535 mm at Air Panas, Segamat rainfall station (Shafie, 2009) and; in January 2011, the highest recorded daily rainfall was 475.3 mm in Segamat on 30th January (Malaysian Meteorological Department, 2011). These rainfall events are considered extremely high when compared with the average monthly rainfall of 200 mm in Johor River basin (Shafie, 2009).

The direct influence of climate change is the change in heavy rains because warmer air can hold more water and in turn this increases the risk of flooding (Trenberth, 2005). Flood is the most destructive natural phenomenon compared to other natural disasters such as earthquakes, volcanoes, etc. (Kundzewicz et al., 1993). However, the occurrence of flood may be due to other factors besides changes in rainfall pattern. These factors include changes in land use, construction of dams and reservoirs, flood mitigation schemes and drainage network systems, etc. In addition, the delineation of catchment area is always challenging due to anthropogenic factors such as the existence of artificial inflows or diversions and the demarcation of effective catchments which are often not necessarily the same as topographic catchment (Musy & Higy, 2010). Hence, this research focuses on rainfall data to avoid the effect of non-meteorological causes and by using flood discharge data in assessing the impact of climate change.

[1] 48-hour maximum rainfall = 18 December 2006 (16:00 hour) to 20 December 2006 (16:00 hour)

[2] 24-hour maximum rainfall = 11 January 2007 (09:00 hour) to 12 January 2007 (09:00 hour)

1.3 PROBLEM STATEMENT

In the Malaysian practice, the Gumbel distribution is used to construct Intensity-Duration-Frequency (IDF) curves using rainfall data for the entire Peninsular Malaysia. Hydraulic structures are mostly designed based on IDF curves (Drainage and Irrigation Department Malaysia, 1994; 2000; 2010). However, Gumbel tends to underestimate the extreme rainfall amount and flood peak because it tends to shift towards the lower values at the upper tail (Koutsoyiannis & Baloutsos, 2000).

With changing climate, it is of critical concern to investigate whether Peninsular Malaysia has experienced more intense rainfall. This is more so given that previous studies (Shafie, 2009; Malaysian Meteorological Department, 2011) have identified changes in trend for the frequency of occurrence and also the intensity in rainfall and flood.

The change in climate and the application of Gumbel distribution in our practice could lead to the under-design of hydraulic structures that provide flood and coastal protection. Hence, this study aims at assessing the hydrologic statistics of rainfall trends and frequency analysis while factoring in impacts from climate change in Peninsular Malaysia to ensure the adequacy of current hydraulic structure designs. It is necessary to study the impacts of extreme hydrological events and minimise their effects on the environment and population by adopting adequate designs for hydraulic structures. Furthermore, frequency analysis is widely used for estimating quantiles based on extreme event records for the design of hydraulic structures.

Furthermore, various rainfall analyses have been conducted to assess the statistics of observed rainfall in Peninsular Malaysia, for instance identifying the best fitted distribution for annual maximum rainfall (Zalina et al., 2002; Wan Zawiah et al., 2009) and assessing the changes in rainfall trends (Wong et al., 2009; Suhaila et al., 2010; Amirabadizadeh et al., 2014). However, these studies were carried out without incorporating with the influence of climate change, which will subsequently affect the design of hydraulic structure, water resources management, etc. In addition, there is a lack of studies combining probability distribution functions and parameter estimation methods that incorporate the impact of non-stationary time series on a regional basis.

1.4 OBJECTIVES

This research focuses on assessing hydrologic statistics of rainfall trend and frequency analysis with impacts from climate change. The work utilises eight different durations of rainfall data that range between 15-minute to 72-hour intervals from 56 rainfall stations in Peninsular Malaysia. The specific objectives of this research are as follows:

1. To determine the possibility of one statistical distribution function that can give adequate fit for rainfall data across Peninsular Malaysia and, for a range of short and long duration rainfall.
2. To examine whether there are changes in trend of rainfall recorded at various rainfall stations in Peninsular Malaysia.
3. To determine the statistical distribution functions that can give adequate fit for rainfall data across Peninsular Malaysia with

hydrologic frequency analysis, by incorporating the impacts of climate change.

4. To evaluate the combination of probability distribution function and parameter estimation method for different regions within Peninsular Malaysia.

1.5 SCOPE OF WORK

The following statistical analyses are carried out in order to assess the statistics of rainfall trend and stationarity of data series, and evaluate the occurrence of hydrologic events based on the records. Statistical tests and descriptive analyses are the methods available to analyse the trends and shifts of the hydrological data.

In this study, Mann-Kendall, Mann-Whitney and Mood's Median tests are adopted to assess the trend or relationship of hydrological variables, especially extreme hydrological events. It is a common practice and numerous studies have been carried out to identify trends and shifts in hydrologic time series to help understand climate change and variability impacts (Chang, 2011; Barua et al., 2013; Zarenistanak et al., 2014). Among the statistical tests available for testing the trends and shifts in hydrological time series, Mann-Kendall trend test is the most frequently used method (Tomozeiu et al., 2000; Mondal et al., 2012). At the same time, Mann-Whitney and Mood's Median tests are adopted to assess the stationarity of the rainfall data.

On the other hand, descriptive analysis approaches assess the trend by comparing the distributions of the hydrologic time series sampled from different sub-periods. By identifying the distribution that best represents the rainfall data, hydrologic frequency analysis evaluates the probability of extreme rainfall events. Since the outcome of hydrologic frequency analysis determines the planning and design of most hydraulic structures, the ability to accurately interpret extreme rainfall events is crucial. Furthermore, the importance of the ability in handling variables has increased in recent years due to the effects of climate change which consequently add complications and increased uncertainty in water resources. In general, frequency analysis is not only used to prevent tragedy but also to improve the efficiency of the design of the hydraulic structures (Kite, 1988). However, not much of these researches compared and analysed the distributions of rainfall time series sampled from different sub-periods (before and after changes begin). Therefore, it is important to integrate the effect of climate change in rainfall estimation to facilitate optimal design of hydraulic structures.

In this study, frequency analyses are carried out with full series data and also two series sampled from different sub-periods to show the influence of climatic trends or cycles in the analysis.

1.6 OUTLINE OF THE THESIS

The thesis is organised in five chapters as follows:

- **Chapter 1 – Introduction** gives a brief introduction of the climate change impact on hydrological events and hydrologic statistical procedures, objectives of this study, as well as the thesis outline.
- **Chapter 2 – Literature Review** covers some selected approaches of hydrologic frequency procedures, reviews on probability distribution functions, parameter estimation methods, assessment procedures, and

statistical analyses commonly used in hydrologic studies. This chapter also covers some studies done on the change in rainfall trends and distributions related with the anticipated climate change.

- **Chapter 3 - Methodology** describes the methods and procedures used, including the statistical analyses used to evaluate changes in rainfall trend, hydrologic frequency analysis and assessment procedures adopted together with justification of the selection. Also, it covers the study area and selection of rainfall data used in this study.
- **Chapter 4 – Results and Discussions** presents the outcomes of study and discusses the results. This includes outcomes of frequency analysis when only the full record length of data is used and, discusses limitations and difficulties in fitting the data. Also, the chapter discusses the results of statistical tests in identifying spatial and temporal changes of rainfall trend. The last section concentrated on the results and discussions from the frequency analysis study using two sub-series data (full series data divided into two sub-series).
- **Chapter 5** concludes the research and offers some recommendations for further research activities in relation to the study on hydrologic frequency analysis.

CHAPTER 2: LITERATURE REVIEW

This chapter consists of three sections. The first part, Section 2.1, provides an overview of hydrologic frequency analysis. This includes the factors that affect the applications of hydrologic frequency analysis, probability distribution functions commonly used in hydrologic frequency study, parameter estimation methods and various assessment procedures that verify the best fitted distribution function. Section 2.2 discusses the trend test and non-stationary test used in hydrologic analyses. The final part Section 2.3 covers some of studies that assess the changes in rainfall trends and distributions.

2.1 HYDROLOGIC FREQUENCY ANALYSIS

There are observational evidences showing that the rainfall trend is changing, but it is difficult to attribute the exact causes for observed changes in rainfall and ascertain if this change persists. One such approach is to measure the presence of change in extreme hydrologic events and represent these events in the form of statistical distributions. The presence of changes can then be detected, for example, in the mean, median or percentiles (Committee on Hydrologic Science; National Research Council, 2011).

Hydrologic frequency analysis is one of the statistical procedures that can be applied to estimate the probabilities associated with design events (Kite, 1988). Hydrologic frequency analysis always attracts the interest of researchers due to its relations with physical hydrologic variables, which provides first-hand information about extreme hydrologic events. Furthermore, extreme events do not only lead to flooding, erosion and sedimentation; but also have direct impacts on planning, design, construction, operation and maintenance to manage and utilise water (Lee, 2004).

Enormous studies have been carried out in hydrologic frequency analysis. Among common researches include the determination of probability distributions that best fit the hydrological variables (Zalina et al., 2002; Su et al., 2008), the determination of the best combination of distribution functions and parameter estimation methods (Park et al., 2000; Seckin et al., 2010), flood frequency analysis (Borujeni & Sulaiman, 2009; Machado et al., 2015) and, regional frequency analysis (Shahzadi et al., 2013; Nam et al., 2015).

The following sections review the complexities of hydrologic frequency analysis and its approaches to hydrologic frequency analysis such as probability distributions, parameter estimation methods and assessment procedures.

2.1.1 Complexities of Hydrologic Frequency Analysis

The complexity of the hydrologic systems and its dependence on uncontrolled variables are causing difficulties in hydrologic frequency analysis application. Among the factors that affect the applications of hydrologic frequency analysis includes types and characteristics of hydrologic data, data collection procedures, as well as seasonal and geographical influence on hydrologic systems. All these factors increase the degree of complexity (with regard to selecting the appropriate distribution to represent data and infer the analysis results efficiently) in hydrologic frequency analysis and lead to difficulty in generalisation of results from the analysis.

2.1.1.1 Data types and characteristics

Different types of rainfall data are applied in frequency analysis for different reasons. Among the numerous types of rainfall data, researches have been carried out using annual average rainfall (Mahdavi et al., 2010), daily rainfall data (Li et al., 2013) and annual daily maximum rainfall (Olofintoye et al., 2009). The annual maximum rainfall data series for various durations (Haktanir et al., 2010) are common in establishing the rainfall-depth-duration relationship for specific study area. Besides, seasonal rainfall series (Parida, 1999; Liang et al., 2012) have been applied for flood control structure operations and for assessing the growing season for crops as flood often occurs during summer in the studied areas.

In the study of extreme hydrologic events, researchers may choose to apply different data series such as annual maximum series (AMS), partial duration series (PDS) or peaks over threshold (POT) and annual exceedance series (AES) in their studies. Each of the data series has its advantages and disadvantages, for instance the AMS might mislead the justification of extreme rainfall if used to determine the appropriate probability distribution for extreme rainfall. This is because there might be other values in a specific year that are less than the amount of maximum rainfall but exceed the largest value of other years (Madsen et al., 1997). PDS on the other hand includes all the highest rainfall events in a certain record length and hence might be able to improve the parameter estimation for the distribution of rainfall data. However, including more data in the analysis does not necessarily guarantee better estimates since the complexity in selecting the threshold level might affect the independence of the selected events (Madsen et al., 1997; Gordon et al., 2004). Meanwhile, AES only consists of the top N events from N-year record and is often presumed that the selected data series may not be fully independent events (Chow, 1953).

Comparing these three types of data series, AMS is more popular among researchers and has been widely adopted in various hydrological frequency analyses due to its simpler structure (Willems et al., 2012). Most of the distribution functions are able to provide a reasonable fit to AMS data for example EV1, GEV and Kappa distributions have been applied in studies using annual maximum rainfall series (Hershfield, 1973; Parida, 1999; Zalina et al., 2002) and LP3 and Wakeby distributions for annual maximum flood data (Griffiths, 1989; Pilon & Adamowski, 1993). For PDS data, only Generalised Pareto and Wakeby distributions are adequate to represent the rainfall series (Su et al., 2008; Wan Zawiah et al., 2009).

Furthermore, some unique characteristics of hydrologic data increase the level of difficulty in the analysis of hydrologic data in addition to escalating the complexity of hydrologic frequency analysis. Such characteristics include a lower bound of zero and the regular presence of outliers with more common outliers on the high side that leads to positive skewness and non-normal distribution of data, seasonal patterns and auto correlation, the occurrence of censored data where data are reported with reference to some threshold and, dependence on some uncontrolled variable (Helsel & Hirsch, 1992).

2.1.1.2 Type of error

Hydrologic data should have tolerable errors, sufficient length of record and be "homogeneous" so that hydrologic frequency analysis can yield a reasonable projection of extreme events based on observed data. There are some common issues in relation to hydrologic data collection that leads to incomplete and missing data and hence, this increases the level of complexity in hydrologic frequency analysis (Interagency Advisory Committee on Water Data, 1982). These issues include the accuracy of the data collected (Chowdhary et al., 1995), issues with the measuring equipment (Strangeways, 1984; Chowdhary et al., 1995); accessibility (Subramanya, 2009) and, non-standard procedures in data collection.

The accuracy of the data is affected by the precision of gauging instrument, site constraint and also the reliability of the data collector (Interagency Advisory Committee on Water Data, 1982; Gordon et al., 2004) while the discontinuity of the recorded data is typically caused by the malfunction of the instrument (Subramanya, 2009). In relation to the data collection procedure, there might be changes in data collection techniques and procedures over time due to the implementation of new systems, site relocation, etc., and this causes non-homogeneity in data records especially for long periods of data collection (Arnell, 2002).

2.1.1.3 Hydrologic systems with seasonal, geographical and anthropogenic influence

Complex interactions between the climatic and topographic characteristics have influenced and affected hydrologic phenomena such as rainfall and runoff to vary over space and time, and such phenomena may be extremely inconsistent and complex at all scales (Sivakumar & Singh, 2011). Hence, it is necessary to investigate the impact of these influences on the current practice in frequency analysis.

In relation to variations of hydrological variables over time and space, differences in hydrological behaviours have not only occurred on an inter-seasonal scale but the transformation also takes place on an inter-annual scale, decadal scale, or even over hundreds and thousands years (Arnell, 2002). For instance, rainfall between May to October each year contribute to about 84% of total annual rainfall in Chia-Nan Plain Area, Taiwan (Lee, 2004) or increased of rainfall rate over the southeastern United States and gulf of Mexico due to the sea surface temperature anomalies in 1971-1990 (Arias et al., 2011).

There are however diverse opinions in relation to the spatial effects. For examples, Prudhomme & Reed (1999) found higher average annual rainfall over mountainous regions compared to plain areas while Lee (2004) suggested that the average annual rainfall is affected by both elevation and distance from the sea. Simon & Mohankumar (2004) on the other hand maintain that the local characteristics of the site could be more influential on the amount of rainfall than altitude. They found that Kumily (1140 m above sea level which is located on the windward slope of a mountain in Kerala, India) received lesser rainfall during south west monsoon than Nerimangalam (200 m above sea level).

The effect of the spatial variation also affects the selection of best fitted distribution function in frequency analysis. For example, Vogel et al. (1993) mentioned that log-Pearson III distribution is able to provide adequate approximations to the distribution of flood flows across the Australian continent. However when the entire continent is divided into several smaller regions, log-Pearson III fails to represent all delineated regions (Arnell, 2002).

2.1.2 Probability Distributions

Under a changing climate, an understanding of the frequency of rainfall extremes is crucial for improving the management of climate-induced risks. The probability of rainfall extremes is a key input and the probability distribution of rainfall extremes is analysed with probability functions. A variety of continuous probability functions have been adopted in studies to determine the frequencies or occurrences of a hydrological event. The reliability of the frequency estimation from limited historical data is very significant to the engineering design of hydraulic structures because the designs are solely based on risk analysis derived from the observed data.

In the following sections, six groups of probability distributions are reviewed in detail which cover important features of the distributions, methods for parameters estimation used, selected case studies and, limitations of the distribution functions. The groups of probability distributions include Extreme Value, Normal, Pearson III, Generalised Pareto, Wakeby and Kappa distributions. Refer APPENDIX 1 for the probability distributions function formulas.

2.1.2.1 Extreme value distributions

Kotz & Nadarajah (2000) cited that the theoretical development of extreme value distribution was developed by Fréchet (1927), Fisher & Tippett (1928) and improved by Gumbel (1958). Extreme value type distributions have been important for extreme hydrologic events. However, there is no clear validation of other distributions to model extreme data even though these may provide a more reasonable fit (Hershfield, 1973). This has inspired researchers to determine which alternative distribution function is more appropriate in representing extreme data among extreme value type distributions. There are three different types of extreme value distributions namely, Extreme Value Type I (EV1), Extreme Value Type II (EV2) and, Extreme Value Type III (EV3) distributions. The development of extreme value type distributions was then developed further by Gnedenko (1943) who provided the theoretical justification for the scale, location and shape parameters for each of these extreme value distributions (Kottegoda & Rosso, 2008).

Among these three extreme value distributions, the two-parameter EV1 has been most widely adopted to model the annual maximum rainfall and flood flow data, for example annual daily maxima rainfall in South Dakota, United States (Hershfield, 1973), annual maximum series with a few rainfall durations in

Nigeria (Oyegoke & Sonuga, 1983) and annual maximum flood flow in Nyanyadzi River, Zimbabwe (Mujere, 2011). In the Malaysian practice, EV1 is used to establish the depth-frequency relationship for annual maximum rainfall series using the method of moments as its estimation method (Drainage and Irrigation Department (DID), 1973). The developed intensity-duration-frequency curves served as a guideline for the design and management of infrastructure in Malaysia. However, EV1 tends to underestimate the amount of extreme rainfall due to its tendency to shift towards the lower values at the upper tail compare to GEV (Koutsoyiannis & Baloutsos, 2000).

Although EV1 is more common in hydrologic study, researchers also used the three-parameter EV2 for rainfall frequency analysis in New Zealand (Pearson & Henderson, 1998) and to model annual flood data in St. Mary River (Heo & Salas, 1996) as well. Shen et al. (1980) compared the results of flood frequency analysis using EV1 and EV2 distributions for more than 200 stations across United States and fitted by maximum likelihood method. They found that EV2 provides a more conservative estimation and is suitable to be used as a design model.

It has been also observed that sometimes more than one distribution function may be needed to represent the rainfall data series of a region. For instance, Pearson & Henderson (1998) discovered that both the EV1 and EV2 distributions give reasonable fit in the frequency analysis of 1-, 6- and 24-hour annual maximum rainfall series to different regions across New Zealand. Even though both distributions have been widely adopted, some of their limitations are worth mentioning. In agreement with Fiorentino et al. (1985), Connell & Pearson (2001) stated that neither the EV1 nor the EV2 distribution can give good estimation for the extreme events because the outliers could be part of another distribution.

EV3 distribution is only suitable for low flow frequency analysis arises due to the characteristic of the data bounded by zero on the left (Pilon, 1990; Caruso, 2000; Vivekanandan, 2011). For the frequency analysis that relates to maxima, Erto (1982) introduced the inverse Weibull distribution to handle the maximum series and it's bounded on the upper side. But the inverse Weibull is rarely used in hydrological application; its application is more noticeable in the field of forestry (Kuru et al., 1992; Liu et al., 1992). The main limitation of the EV3 family distribution lies in the challenge to obtain a suitable parameter estimation method for the inverse Weibull distribution though much effort have been devoted on exploring the suitable parameter estimation methods for the inverse distribution (Marusic et al., 2010; Gupta & Kundu, 1999).

The Generalised Extreme Value (GEV) was enhanced by Jenkinson (1955) by combining three extreme value distributions into one formula (Bobée et al., 1993). The GEV distribution is a three-parameter generalised distribution that comprises three special cases of EV1, EV2 and EV3 distributions where each of them are distinct by the shape parameter (κ). The GEV satisfies different types of extreme meteorological data especially when it is uncertain about fitting the observed data to which type of extreme value distribution (Jenkinson, 1955).

The GEV distribution appears to outperform other extreme value distributions and is a popular choice in modelling the annual maximum rainfall series. Among some case studies that have found GEV superior include annual maximum rainfall for 17 stations in Peninsular Malaysia (Zalina et al., 2002); annual maximum rainfall series in North East of India (Muller et al., 2007); and Athens (Koutsoyiannis & Baloutsos, 2000). It also has been recognised as standard distribution function for some government institutions. For example, the application of maximum likelihood method to the GEV distribution is recommended by Natural Environment Research Council (1975) for use in flood frequency analysis for Britain and Ireland (Bobée et al., 1993).

Even though GEV has been widely adopted in frequency analyses, some results indicate that the EV1 provides a better fit to annual maximum rainfall data compared to GEV. Nadarajah & Choi (2007) found EV1 is a better option with the best estimation results for four of the five selected rainfall stations across South Korea when evaluating the suitability of EV1 and GEV distributions using annual maximum daily rainfall data. In a comparison study between GEV and EV1, Zalina et al. (2002) pointed out that GEV will lead to a more conservative estimation for extreme events and will give a higher estimation for more skewed data but and a lower estimation for less skewed data compared to EV1.

The two-component extreme value distribution (TCEV) has also been found to be suitable for heavy tailed data sets (Rossi et al., 1984). The TCEV was derived from two EV1 distributions which consist of four parameters. It represents two different series of data, whereby one represents the more frequent normal events while the other represents rare extreme events (Connell & Pearson, 2001). TCEV is often applied in regional frequency analysis where encouraging results have been obtained from both regional flood and rainfall frequency analysis. For example, the outcomes indicate reasonable quantiles estimation for New Zealand (Connell & Pearson, 2001) and; the regional frequency analysis for annual maximum daily rainfall in Tuscany, central Italy (Tartaglia et al., 2006) and; analysis using one hour and 24 hours maximum rainfall for four regions in southern Italy (Ferro & Porto, 1999). The TCEV distribution is unsuitable for quantiles estimation of very high return period (more than 100 years) especially if the flood population is upper bounded or the existence of flood upper bound (probable maximum flood) (Botero & Francés, 2010).

From the researches carried out on these extreme value distributions, GEV appears to be better choices in fitting the extreme rainfall in most of the cases.

2.1.2.2 Normal distributions

The normal distribution is indeed the most popular distribution and has been used in most of the population models (Casella & Berger, 2002). However, it is only useful in fitting symmetrical types of hydrologic data (Stedinger et al., 1993) and in the analysis of random errors (Yevjevich, 2010). It is not suitable for handling extreme hydrologic variables with short record length that are usually asymmetrical.

In the presence of outliers due to the occurrence of extreme hydrological events, the data will exhibit positive skewness and a non-normal distribution

(Helsel & Hirsch, 1992) and hence, log-normal distributions have been used to capture this feature. By using a logarithmic transform of the data, log x is applied to the principles of normal distribution. This reduces the skewness and the logarithmic transform will lead to the derivation of two-parameter log-normal (LN2) and three-parameter log-normal (LN3) distributions.

Sangal & Biswas (1970) found LN2 lacking in consistency compared to LN3. Their results indicated that the logarithm of the annual flow data from the stations were all negatively skewed but the LN2 distribution assumes zero skewness with a tendency for higher order approximations. Hence, the application of LN2 in flood frequency analysis is less popular after the 1980s due to its limitation in fitting the flow data (Singh, 1998).

Stedinger (1980) has expressed the skepticism on the performance of the parameter estimation method with LN3 over the LN2 distribution. For instance, the maximum likelihood method does not always provide a reasonable solution to the likelihood equation of LN3. This is in-line with the statement by Giesbrechta & Kempthorne (1975) who showed that the simple likelihood equation of LN3 may give asymptotic errors (Stendinger, 1980).

2.1.2.3 Pearson III distributions

Karl Pearson developed the Pearson types of distributions to handle skewed data sets (Pearson, 1895). This section focuses on Types III of Pearson’s distributions which include both the Pearson Type III (P3) and Log-Pearson Type III (LP3) distributions.

Foster (1924) is known as the pioneer in the practical application of asymmetrical distribution function for flood analysis, and Pearson type I and III distributions were applied to illustrate the frequency distribution of annual floods (Dalrymple & Benson, 1960). Other applications of P3 include modelling of annual maximum precipitation for the development of Intensity-Duration-Frequency (IDF) curve in China by using a curve-fitting method for parameters estimation (AP-FRIEND, 2005) and, modelling of short duration rainfall and development of IDF relationships for Sylhet City, Bangladesh (Rashid et al., 2012). However, when the coefficient of skewness for the sample is negative, P3 will be bounded at the upper end and hence, is not suitable for maximum events (Kite, 1988).

Similar to log-normal distributions, the transformed variable log x is applied to the P3 distribution to produce the reduced skewness distribution, LP3. The LP3 has been widely used in hydrology, primarily because it has been recommended for application to flood flows by the US Water Resources Council in 1967 (Huynh & Hira, 1983; Chin, 2000) and by Australian Institution of Engineers in 1977 (Srikanthan & McMahon, 1981). Vogel et al. (1993) mentioned that for modelling of annual maximum flood flows in Australia, LP3 is able to provide adequate approximations to the distribution of flood flows across the continent.

Apart from United States and Australia, the LP3 distribution has also been applied in hydraulic studies for Canada and Turkey (Huynh & Hira, 1983; Izinyon et al., 2011). Srikanthan & McMahon (1981) showed that the estimated quantiles by LP3 may be affected by the size of the sample and recommended using a larger sample size to reduce the sampling bias. Millington et al. (2011) on the other hand pointed out that LP3 seems to underestimate the upper bound of the distribution when the distribution is positively skewed and overestimate it when it is negatively skewed. Underestimating the value of the upper bound may adversely affect the estimation of extreme events.

2.1.2.4 Generalised Pareto distribution

The generalised Pareto (GP) distribution was introduced by Pickands (1975) to construct a threshold model that describes the exceedance of threshold for hydrological data. Among Pareto type distributions, the two-parameter generalised Pareto (GP2) and the more general three-parameter generalised Pareto (GP3) distribution have been frequently used in hydrologic frequency analysis. The third parameter of the GP3 is the location parameter that serves as a threshold or lower boundary value of x.

Davison & Smith (1990) pointed out that the GP distribution can be used for modelling high level exceedance. Some researchers applied the GP2 distribution for modelling excesses over threshold (Hosking & Wallis, 1987; Rosbierg et al., 1992). Besides, the GP3 distribution has been adopted in frequency analyses using partial duration series of dry-spell and daily rainfall with its parameters estimated using the L-moments method (Lana & Burgueno, 1998; Wan Zawiah et al., 2009). However, Western et al. (2011) pointed out that the third parameter of GP3 does significantly improved the fitting of the rainfall data.

Other researchers compared the estimation by GEV and GP using AMS and PDS on various types of hydrologic data. Among the examples of applications include flood peaks of River Nidd in England (Hosking & Wallis, 1987), rainfall data with 50 rainfall stations that focus more on the west coast of Peninsular Malaysia (Wan Zawiah et al., 2009) and annual maximum dry-spell in Spain (Lana & Burgueno, 1998). The GP distribution is only suitable to model hydrologic data with high frequencies due to its characteristic with a long and thick upper tail (Teodorescu, 2010). Hence, the Pareto model is less flexible and fails to model annual maximum series or average data.

2.1.2.5 Wakeby distribution

The five-parameter Wakeby distribution was introduced by Houghton (1978) to imitate the shape of skewed distributions and hence, provide a more flexible fit than the conventional two or three-parameter distributions. The Wakeby distribution is often defined by its quantile function because the probability density function of Wakeby is not clearly defined (Griffiths, 1989; Tarsitano, 2005). Hence, the L-moments parameters estimation method is used to fit the five-parameter Wakeby distribution. Since this involves explicit expressions for the parameters; x=x(F) can only be acquired by the L-moments method but not by the method of moments nor by the maximum likelihood method. Furthermore, the measures of scale and shape parameters can be obtained directly using the L-moments method (Su et al., 2008).

Interestingly, Park et al. (2000) encountered situations when L-moments failed to yield the five-parameter estimation for annual maximum rainfall data from 19 out of 61 stations due to a convergence failure in the Newton-Raphson iteration. This prompted Park and co-workers to develop the maximum likelihood method as alternative. Öztekin (2011) on the other hand, explored the viability of the numerical least squares method as a parameters estimation method for annual peak flows of the Turkish river to overcome this same issue. The least squares method can be used as an alternative when the L-moments method fails to converge but it does not outshine the L-moments method in terms of high return period quantile estimation (Öztekin, 2011).

Wakeby distribution has been applied in frequency analysis for different types of hydrological data (Park et al., 2001; Su et al., 2008) and different data series (Öztekin, 2007). Houghton (1978) showed that Wakeby is superior to the LN3 distribution in modelling flood flows due to its ability in adapting different shapes of distribution as well as its ability to demonstrate the separation effect. In addition to flood frequency analysis, the Wakeby distribution has been able to provide reasonable fits for numerous rainfall frequency studies. This includes the studies at Yangtze River Basin in China, South Korea and Turkey in which the L-moments method was used as the parameter estimations method (Su et al., 2008; Park et al., 2001; Öztekin, 2007).

For different types of data series, various studies have showed the versatility of the Wakeby distribution to represent both annual maximum series (AMS) and partial duration series (PDS) rainfall data. Öztekin (2007) compared the Wakeby with beta-κ and beta-P distributions using AMS and PDS rainfall data for the northeast and southeast region of the United States. It was found that the Wakeby distribution is more suitable to model both the AMS and PDS rainfall series especially at the upper tail of the distribution.

The Wakeby distribution is useful but it has its limitations. In particular, its probability distribution function is not explicitly defined and consequently, the moment estimation of its parameters is impossible while the parameters estimation by maximum likelihood method can be difficult to obtain (Rao & Hamed, 2000).

2.1.2.6 Kappa distribution

The four-parameter Kappa distribution is a generalised function for several two and three-parameter distributions such as GP, GEV and EV1 distributions but with different values of shape parameters (h and k) that allow it to give a better fit to data that was previously poorly fitted by other two- or three-parameter distributions (Hosking, 1994). Table 2.1 summarized the distributions generated by four-parameter Kappa distribution with different values of h and k.

Table 2.1: Summary of distributions generated from Kappa Distribution

h	**k**	**Distribution**
1	$\neq 0$	three-parameter generalised Pareto distribution
0	$\neq 0$	three-parameter generalised extreme value distribution
-1	$\neq 0$	three-parameter generalised logistic distribution
1	0	two-parameter exponential distribution
0	0	two-parameter EV1 distribution
-1	0	two-parameter logistic distribution
1	1	two-parameter uniform distribution
0	1	two-parameter reverse exponential distribution

Numerous works has been performed using the four-parameter Kappa distribution and found the Kappa distribution suitable for hydrologic studies. Among some selected case studies include fitting the Kappa distribution with 2-, 6- and 24-hour duration annual maximum precipitation data in Washington using the L-moments method (Hosking, 1994), modelling of summer monsoon rainfall in India (Parida, 1999) and, fitting the annual maximum rainfall series in South Korea (Park & Jung, 2002). These studies indicated positive results from hydrologic studies using the four-parameter Kappa distribution. For example, the Kappa distribution is preferred over the GEV distribution because it gives higher estimation on higher quantiles, a particularly significant feature in dam safety studies (Hosking, 1994) and, its ability to represent the inter-annual variability of the rainfall series in India (Parida, 1999). The Kappa distribution is also useful for regional frequency analysis especially in validating the homogeneity of a group of sites because a more general distribution is needed to represent the simulated data of a homogeneous region (Hosking & Wallis, 1993).

On the downside, the Kappa distribution suffers from a high level of complexity due to the number of parameters. In this case, the method of moments is unstable especially for small sample sizes while the L-moments method may fail when the shape parameter of the Kappa distribution, h, is greater than negative one (-1) (Park & Jung, 2002). The maximum likelihood method on the other hand, is intractable for computation especially when the likelihood function does not exist which occurs when the values for shape parameter, h and k are greater than one (Park & Jung, 2002).

2.1.2.7 Discussions

With the improvement in computational power, works in hydrologic analysis indicate a trend towards the development of multi-parameter distributions instead of the conventional distributions with only two or three parameters. Among these multi-parameter distributions are the four-parameter Kappa and TCEV distributions (Parida, 1999; Francés, 1998) and five-parameter Wakeby distribution (Su et al., 2008). Table 2.2 summarised the properties of distribution functions commonly used for frequency analysis.

Table 2.2: Summary of Distribution Functions' Properties Commonly Used in Frequency Analysis

Distribution functions	Number of parameter	By	Hydrologic Data	Data Series
Gumbel (EV1)	2	Gumbel	flood flow and rainfall	AMS
Fréchet (EV2)	3	Fréchet	rainfall	AMS
Weibull (EV3)	3	Weibull	low flow	AMS
Generalised Extreme Value (GEV)	3	Jenkinson	rainfall	AMS
Two Component Extreme Value (TCEV)	4	Rossi et al.	flood flow and rainfall	AMS
Lognormal II (LN2)	2	Hazen	flood flow	AMS
Lognormal III (LN3)	3	Chow	flood flow	AMS
Pearson III (P3)	3	Pearson	flood flow	AMS
Log Pearson III (LP3)	3	Pearson	flood flow	AMS
Generalised Pareto (GP)	3	Pickands	flood flow and rainfall	PDS
Wakeby	5	Houghton	flood flow and rainfall	AMS and PDS
Kappa	4	Hosking	rainfall	AMS

Houghton (1978) however expressed skepticism about the adoption of distribution functions with more than three parameters because it may induce greater errors in the estimation process since the parameters of these distributions are often vaguely known. This finding from Houghton is in line with Rao & Hamed (2000) with regard to the five-parameter Wakeby distribution and Park & Jung (2002) with regard to the four-parameter Kappa distribution. In addition, Park et al. (2001) mentioned that the selection of the distribution function to represent extreme hydrological events does not really rely on the number of parameters even though distributions with more parameters are known to be more flexible in fitting the hydrologic data. This is in line with other researchers for example, the three-parameter GEV is selected in preference to five-parameter

Wakeby distribution in representing the annual extreme rainfall series in Peninsular Malaysia (Zalina et al., 2002) and EV1 provides better estimation compared to GEV for extreme rainfall in Seoul (Nadarajah & Choi, 2007).

This shows that besides the parameters, the selection of distribution function for hydrologic analysis over a study area may be affected by other factors such as local climatic and geographical characteristics of the site. For example, in selecting the probability distribution for modelling annual maximum flood flows in Australia, Vogel et al. (1993) found GP and LP3 was only able to provide adequate approximations to the distribution of flood flows across the continent. However, when the entire continent is divided into several smaller homogeneous regions, different distribution functions were required to fit each region. In their work, GEV was found suitable to fit flood flow data in Tasmania and the southwest coast while GP gives a reasonable fit to the urbanised area in the south-eastern coastal region. In this case, variations in hydrological behaviour between catchments may be due to differences in climate regime and catchment physical properties (Arnell, 2002).

The choice of the underlying frequency distribution has a significant effect on quantile estimates (Ware & Lad, 2003). The distributions are often chosen due to their flexibility in mimicking the shape of an observed statistical distribution especially for regional frequency analysis (Houghton, 1978; Hosking, 1994). In the study of rainfall series, the interest is focused on the estimation of the extreme right-hand tail of a distribution. In general, the advantages and disadvantages of each distribution function are shown in Table 2.3.

Table 2.3: Advantages and disadvantages of distribution functions commonly used in frequency analysis (Connell & Pearson, 2001; Sangal & Biswas, 1970; Millington et al., 2011; Griffiths, 1989; Hosking, 1994)

Function	Advantages	Disadvantages
EV1	• Two-parameter is easier for computation	• Underestimates extreme rainfall compare to GEV
EV2	• Provides a more conservative estimation and is suitable to be used as design model	• More skewed at upper tail and tends to overestimate
EV3	• Only suitable for low flow	• Less applicable
GEV	• More robust • Suitable for regional analysis	• Provides lower estimates for less skewed data compared to EV1
TCEV	• Regional analysis	• Not suitable for quantiles estimation of very high return periods
LN2	• Reduces the skewness	• Inconsistent compare to LN3 • Zero skewness with tendency for higher approximations
LN3	• Performs better than LN2	• Scepticism on the performance of maximum likelihood method of LN3 over the LN2
P3	• Practical for asymmetrical distribution functions especially in flood analysis	• If coefficient of skewness for the sample is negative, it will be bounded at the upper end and hence, is not suitable for maximum events
LP3	• Reduces the skewness compared to P3	• Underestimates the upper bound of the distribution when the distribution is positively skewed and overestimates it when it is negatively skewed.
GP	• Long and thick upper tail for modelling high level exceedance	• Less flexible and fails to model annual maximum series or average data

Function	Advantages	Disadvantages
Wakeby	• More flexible fit than the conventional two or three-parameter distributions	• Probability density function of Wakeby is not clearly defined, hence is not suitable with the method of moments and maximum likelihood method.
Kappa	• More flexible fit than the conventional two or three-parameter distributions	• Difficult to find a suitable parameter estimation method under certain circumstances

In this study, only distributions with two and three parameters are chosen as candidate distributions. This is because the distribution functions with more parameters, for example four-parameter Kappa and, five-parameter Wakeby distributions may induce greater errors in the estimation process as these extra parameters are often not clearly identified (Houghton, 1978).

2.1.3 Parameter Estimation Methods

Since hydrological processes are random in nature, statistical parameters are useful in projecting the central tendency and variability of a probability distribution (Hong, 2009). Therefore, aside from the emphasis on which type of distribution function should be adopted in fitting related hydrological data, methods of parameters estimation have been studied as well. However, the competency of the parameter estimation methods is subjected to the choice of distribution functions and sample size (Martins & Stedinger, 2000).

2.1.3.1 Method of moments

The method of moments is a relatively old and perhaps the simplest method for parameters estimation commonly used in statistics. Essentially, the idea consists of taking a linear functional equation and representing it by a linear matrix equation, a technique that was developed almost a century ago (Harrington, 1990; Wooldridge, 2001). Through the voluminous studies that have been carried out in the field of statistics, this method is becoming less and less relevant. Wilks (2006) stated that the method of moments does not fully utilise the information in the data set and it causes the value of the estimated parameters to become unreliable. Moreover, the traditional moment-based measure of skewness, γ, is difficult to estimate if the distribution is distinctly skewed; it is too sensitive to the extreme tails compared to the L-moments method according to Hosking (1990). Hence, the method of moments is less suitable to estimate parameters for distribution with more than two parameters.

2.1.3.2 Method of maximum likelihood

The method of maximum likelihood estimates the parameters by maximising the likelihood function in which the probability of the observed data gains the highest probability (Rice, 2007).

According to In (2003), maximum likelihood estimation does not require or only needs very few distribution assumptions to summarise observed data by its moments and it also gives smaller variance (Suhaila & Jemain, 2007b). Therefore, the maximum likelihood estimation is still widely adopted in practice (Suhaila & Jemain, 2007a; Suhaila & Jemain, 2007b; Park & Jung, 2002; Nadarajah & Choi, 2007). However, maximum likelihood estimation is not suitable for five-parameter Wakeby distribution because the probability distribution function of Wakeby is not clearly defined (Park et al., 2001).

2.1.3.3 L-Moments method

The L-moments method was introduced by Hosking (1990) for hydrological data analysis. According to Hosking (1990), the L-moments method is more robust to the existence of outliers in the data, is sturdier in its adaptability to a wider range of distributions and is more accurate for data with small sample size. Furthermore, the L-moments method would not exaggerate the value because this method does not raise the number to power (Koutsoyiannis & Baloutsos, 2000).

Due to the above mentioned advantages, the L-moments has been applied to different regions, for example India (Parida, 1999), Korea (Park & Jung, 2002), China (Su et al., 2008) using precipitation data, and using flood data in Iran (Borujeni & Sulaiman, 2009), Canada (Yue & Wang, 2004). In a local context, several studies were also carried out using L-moments in Peninsular Malaysia (Zalina et al., 2002) as well as east Malaysia (Lim & Lye, 2003).

L-moments is found to be an effective approach in hydrological statistics studies carried out internationally using different types of data, such as stream flow data (Borujeni & Sulaiman, 2009), rainfall data (Koutsoyiannis & Baloutsos, 2000; Parida, 1999) and number of days without rainfall - dry-spell data (Nasri & Moradi, 2011). Moreover, the estimation of parameters for generalised extreme value distribution using the L-moments method has a lower root-mean-square error compared with the maximum likelihood method (Hosking et al., 1984).

2.1.3.4 L-Moments related methods

Ever since the L-moments method was introduced by Hosking (1990), several extensions of L-moments have been developed along the way, including LQ-moments (Mudholkar & Hutson, 1998) and Trimmed L-moments (TL-moments) (Elamir & Seheult, 2003).

LQ-moments is developed for the estimation of Kappa parameters, and according to Shabri & Jemain (2010), LQ-moments is able to give an estimation for the Kappa distribution whereas sometimes L-moments fails to give a reliable estimation. Another study has been carried out to compare the robustness of conventional L-moments with LQ-moments in finding the most suitable distribution to fit the annual maximum daily rainfall in Peninsular Malaysia (Wan Zawiah et al., 2009).

The TL-moments method is quite beneficial in parameter estimation for data with outliers and for distributions that do not have a second-order moment (mean) such as the Cauchy distribution (Elamir & Seheult, 2003). However, Shabri & Mohd Ariff (2010) found that in the study of identifying the most suitable distribution for annual maximum rainfall by L-moments and TL-moments, L-moments method still be able to give a more precise result. Yet, the result of parameters estimation by these two methods does not differ significantly.

Therefore, it is acceptable to use either TL-moments or LQ-moments to replace L-moments as the parameter estimation method (Shabri & Mohd Ariff, 2010; Wan Zawiah et al., 2009).

In short, the advantages and disadvantages of the previously mentioned parameter estimation methods are as shown in Table 2.4.

Table 2.4: Advantages and disadvantages of parameter estimation methods

Function	**Advantages**	**Disadvantages**
Method of Moments	• Easy to compute	• Easy to give accurate estimation if the distribution is distinctly skewed • Less appropriate for distribution with more than two parameters
Maximum Likelihood	• Required minimum distribution assumptions • Smaller variance	• Less appropriate for Wakeby distribution
L-Moments	• More robust to the existence of outliers	• The performance is not consistent with Kappa distribution
L-Moments Related Methods	• Robust with the existence of outliers • Suitable for distributions that do not have second-order moments	• Lesser studies on these methods

2.1.4 Assessment Procedures

2.1.4.1 Graphical methods

Probability plot, quantile-quantile plot (Q-Q plot) and moment ratio diagrams are among the frequently used graphical/visual based assessment tools in evaluating the suitability of a theoretical distribution in representing the hydrologic variables.

The probability plot and the plotting position formula were introduced by Hazen in 1914 and it has been widely used in hydrologic studies (Vogel, 1986).

The graphical method associates the magnitude of events to the probability of occurrence. It can be used to detect outliers and to assess the suitability of a hypothesis distribution to fit observed data (Nguyen et al., 1989).

The probability plot and plotting position formula have been adopted for the assessment of the fitness of a given distribution function to denote the variables in frequency analysis study. For instance, Gumbel (1941) used probability plot to assess the fitness of the annual maximum flood data with EV1; Jenkinson (1955) reviewed the observed flood data that has been transformed by the Hazen plotting formula and compared it with generalized extreme value; Sangal & Biswas (1970) adopted Weibull plotting probability to represent the observed distribution and LN3 as the theoretical distribution in the probability plot. However, the probability plot is unsuitable for the evaluation of distributions with more than two parameters and hence, a more effective Q-Q plot has been recommended (Nadarajah & Choi, 2007).

The Q-Q plot has been found to be more robust than the probability plot because it reduces the problem of assessing how far points cluster near the theoretical distribution line in addition to avoiding the need to compare various curves in the probability plot for distributions with three parameters (Wilk & Gnanadesikan, 1968). Laio et al. (2009) pointed out that there will always be elements of subjectivity in assessing how far empirical points cluster from the theoretical points even though the same plotting position formula is used.

The Q-Q plot was applied to evaluate the suitability between EV1 and GEV distributions in representing annual maximum precipitation data that was transformed using Blom's formula for China and South Korea (Feng et al., 2007, Nadarajah & Choi, 2007).

The conventional moment ratio diagram shows the relationships between various distributions in terms of the shape parameter and by plotting the coefficient of skewness and kurtosis of the sample data on the same diagram, this provides an indication of the ability of the distribution in representing the shape of the sample data (Bobee et al., 1993).

However, the moment ratio diagram was later replaced by the L-moments diagram when Hosking (1990) introduced the L-moments and L-moments diagram for regional frequency analysis. The L-moments diagram is useful in choosing the appropriate distribution function for modelling the hydrological data. Thus, Yue & Wang (2004) suggested that the L-coefficient of variation and L-skewness should be plotted for the evaluation of the suitability of the two-parameter distribution along with the L-skewness and L-kurtosis for three-parameter distributions.

Both the moment ratio diagram and the L-moments diagram can be used to identify the parent distribution for regional frequency analysis (Rao & Hamed, 2000; Peel et al., 2001; Deka et al., 2009; Wan Zawiah et al., 2009) as well as providing a guide in setting boundary to various distributions within a model (Vargo et al., 2010). The L-moment ratio diagram involves plotting the sample L-moment ratios as a scatterplot and by comparing them with theoretical L-moment ratio curves of candidate distributions (Hosking & Wallis, 1997). Distribution selection for regional data is best based on the regional (sample) average. The regional average is the mean value of the L-skewness and L-kurtosis of the sample. In this study, the L-skewness and L-kurtosis of all sites in the region are shown in the L-moments ratio diagram along with the plot of potential distributions.

Vogel & Fennessey (1993) stated that the moment ratio diagram can be biased if the sample size is small (less than 100) or too huge (more than 1000). The L-moments parameter estimation method, on the other hand, is almost unbiased in the construction of moment ratio diagram and, thus more popular in regional frequency analysis.

Among the graphical methods, the L-moments ratio diagram has been found useful in the selection of distributions for hydrologic frequency analysis (Vogel & Wilson, 1996; Borujeni & Sulaiman, 2009; Deka et al., 2009; Wan Zawiah et al., 2009). For instance, LN3 is selected as the best fitted distribution among several three-parameter distributions such as Generalised Logistic, GEV, GP and P3 for modelling peak annual discharge at north Karoon, Iran using the L-moments plot (Borujeni & Sulaiman, 2009). In the same way, Deka et al. (2009) found that the L-moment diagram is useful in choosing GP for annual maximum rainfall in north east India. Wan Zawiah et al. (2009) also concluded that the partial duration and annual maximum rainfall series in Peninsular Malaysia are well fitted by GP and GEV distributions respectively using the L-moment diagram.

In general, graphical methods are a visual evaluation tool that are more suitable for initial assessment due to the element of subjectivity since these methods are generally found to be ill-equipped to give a clear indication on the statistical significance of the fit especially when dealing with several hypothesis distributions (Tao et al., 2002).

2.1.4.2 Goodness of fit tests (GOF)

The GOF method is one of the most widely used approach in identifying suitable distribution functions for frequency studies and quite often researchers tend to combine a few GOF tests to conduct the evaluation. There are some goodness of fit (GOF) statistics such as chi-square (χ^2), Kolmogorov-Smirnoff (KS), Cramér-von Mises (CvM) and Anderson-Darling (AD) tests that compare the hypothesis distribution with the empirical distribution function which is estimated based on the data (Dan'azumi et al., 2010; Haktanir et al., 2010; Seckin et al., 2010). The analyses of the GOF statistics are useful in evaluating the acceptance of the null hypothesis based on the critical values at the required significance level. These procedures can be used in assessing two or more candidate distributions but they are not model discrimination tests that can be used for the selection of the best fitted distribution among the candidate distributions.

The χ^2 statistic measures how well the empirical histogram of the observed data fits against the expected frequency from the fitted distribution. The chi-square statistic is calculated as follows:

$$x^2 = \sum_{i=1}^{N} [O(i) - E(i)]^2 \big/ E(i) \tag{1}$$

where *O(i)* and *E(i)* are the observed and expected frequency of the i^{th} histogram class, and *N* is the number of class intervals divided.

The value of χ^2 statistic is dependent on the number of class intervals (Haktanir, 1991). The number of class intervals divided will affect the ranking between the tested distribution types but there is no specific rule for determining the number of classes. Reddi (1997) mentioned that the number of class should be divided to at least five classes, and if the sample size is large, the number of class maybe divided following this equation below:

$$k = 10 + 1.33\ln(n) \tag{2}$$

where the *k* is the number of class and *n* is the sample size.

The length of each class intervals may be identical or different. In the latter case, Haktanir et al. (2010) suggested to divide the class intervals in such a form that each class will correspond with equal-probability-area and the chi-square statistic formula is simplified to:

$$x^2 = \frac{N}{k} \sum_{i=1}^{N} O(i)^2 - k \tag{3}$$

where the *O(i)* is the observed frequency of the i^{th} histogram class, and *N* is the number of class intervals divided while *k* is the sample size.

In addition, Mann and Wald (1942) have suggested equivalent class intervals and develop a formula for the optimal choice of the number of classes as follows:

$$k = 3.765(\mathrm{N} - 1)^{0.4} \tag{4}$$

The advantages of the Mann and Wald (1942) technique are that the application of the formula removes the subjective element from the choice of the number and width of the classes and equivalent classes are easy to use and lead to unbiased tests.

In addition, Laio (2004) commented that χ^2 is the weakest test among the KS, probability plot, L-moments based test, CvM and AD when: (i) the sample size is relatively small; (ii) the tested distribution function with more parameters and (iii) the parameters are estimated.

For KS, CvM and AD statistics, these are the GOF tests that measure the difference between the empirical cumulative distribution function and the hypothesized cumulative distribution function using a different measure of discrepancy between the empirical and hypothesized distributions. As for the KS statistic, it is defined as:

$$D_N = \max[|F_N(x) - F(x)|] \tag{5}$$

where the $F_N(x)$ and $F(x)$ are the sample and hypothesis distribution function, while N is the sample size. The hypothesis distribution will not be rejected when the computed D_N from the sample distribution is less than the tabulated value of D_N at the required significance level.

As for the KS test, the critical value varies with the size of the sample (n), and it is calculated as:

$$\text{Critical value corresponding to 10\% significance level} = {}^{1.22}\!/_{\sqrt{n}} \tag{6}$$

The critical value for other significance level, α is defined as:

$$\text{Critical value corresponding to } \alpha \text{ level} = \frac{\sqrt{-0.5\ln(\alpha/2)}}{\sqrt{n}} \tag{7}$$

The χ^2 and KS test have been widely applied in hydrologic frequency analysis to determine the best fitted distribution due to its ease of computation (Adeyemi, 2009; Evans et al., 2008). In addition, the χ^2 can be used with either discrete or continuous distribution functions while the KS, AD and CvM only apply to continuous distributions (Zibran, 2012). On the other hand, the KS test seems to be a more powerful test to be used to compare to χ^2 when the sample size is small (Lilliefors, 1967).

The KS test only measures the largest vertical difference (largest deviation) between the observed distribution and the theoretical fitted distribution. Hence, it does not account for the fitting of theoretical distribution over the whole possible range (Vose, 2010) which the observed and expected frequencies may be widely diverging.

Both the CvM and AD tests are quadratic empirical distribution function statistics that measure the discrepancy between two distribution functions. These tests involve the sum of squares of the discrepancy between the empirical and theoretical distribution but the AD test has an additional weight function that accentuates differences in the upper tails. The mathematical expression of CvM and AD statistics can be expressed as:

$$CvM = \int_{-\infty}^{\infty} [F_N(x) - F(x)]^2 dF(x) \tag{8}$$

$$AD = n \int_{-\infty}^{\infty} \frac{[F_N(x) - F(x)]^2}{F(x)\{1 - F(x)\}} dF(x) \tag{9}$$

where the $F_N(x)$ and $F(x)$ are the sample and hypothesis distribution function, while the N is sample size.

The AD and CvM tests can be applied to any distribution function but the critical values of the tests are dependent on the candidate distribution function that is being assessed (Wadagale et al., 2011). Furthermore, the tabulated values and formulas of critical value for several distributions have been published and the AD test statistic has to be adjusted with a constant (which usually depends on the sample size) for Normal, log-normal, Exponential, Weibull, Logistic and EV1 distributions (Stephens, 1974: 1976; 1977a; 1977b; 1979). To avoid the recalculation of critical value for different distribution functions, Laio (2004) provided justification for transforming the test statistics for CvM and AD as the assessment of EV1, EV2, Normal, LN2, GEV, three-parameter Gamma, and LP3 that are commonly used in extreme value analysis and the test statistics are independent of the distributions. Moreover, the additional weight function that gives to the tail of distribution for the AD test is also useful in detecting outliers (Choulakian & Stephens, 2001; Deidda & Puliga, 2006).

The above mentioned GOF tests have been applied to assess the probability distribution in representing extreme hydrologic events. For instance, Su et al. (2008) used only KS test to determine that the Wakeby distribution is the most suitable distribution among GEV, GP and the Generalised Logistic distributions for annual maximum daily rainfall at the Yangtze River Basin in China. Griffiths (1989) accepted the Wakeby distribution to represent the annual maximum flood flow for Waimakariri River in New Zealand by using two GOF tests namely χ^2 and KS at the 95% confidence level. Seckin et al. (2010) adopted three GOF tests such as χ^2, KS and CvM tests to evaluate the suitability of LP3, LN3, GEV and Wakeby corresponding to L-moments and maximum likelihood methods to fit the annual maximum flood peak series for ten stations in Ceyhan River basin, Turkey. Ben-Zvi (2009) used the AD test to determine the suitability of GP to represent partial duration rainfall series for derivation of IDF curves in Israel.

From the literature, it is also observed that the GOF tests are commonly conducted at 5% or 10% significance level in frequency analysis studies (Griffiths, 1989; Dan'azumi et al, 2010; Seckin et al., 2010). In other words, the usage of 5% or 10% level as conventions indicates that these values are a feasible level in frequency analysis studies.

2.1.4.3 Statistical error indices

When the graphical approaches fail to provide conclusive evidence, several statistical error indices have been introduced to compare the modelled outcomes with the observed values by applying the plotting position formula as the empirical distribution function. The root mean square error (RMSE), relative root mean square error (RRMSE), maximum absolute error (MAE), relative absolute square error (RASE), relative mean absolute error (RMAE) and probability plot correlation coefficient (PPCC) are among the error indices commonly used as the assessment method in frequency analysis (Tao et al., 2002; Zalina et al., 2002; Deka et al., 2009). Along the way, RASE, RMAE and PPCC have been suggested by other researchers to measure the difference between the observed values and the expected values. The mentioned criteria are defined mathematically as:

$$RMSE = \left[\sum {(x_i - y_i)^2}/{n}\right]^{1/2} \tag{10}$$

$$RRMSE = \left[\sum {\left({x_i - y_i}/{x_i}\right)^2}/{n}\right]^{1/2} \tag{11}$$

$$MAE = max(|x_i - y_i|) \tag{12}$$

$$RASE = ln \sum \left|{x_i - y_i}/{x_i}\right| \tag{13}$$

$$RMAE = \frac{1}{n} ln \sum \left|{x_i - y_i}/{x_i}\right| \tag{14}$$

$$PPCC = {\sum[(x_i - \bar{x})(y_i - \bar{y})]}/{[\sum(x_i - \bar{x})^2 (\sum(y_i - \bar{y})^2)]^{1/2}} \tag{15}$$

where the x_i and y_i are the observation value and the values computed from assumed empirical probability distribution based on the plotting position formula respectively; n is the sample size; while $\bar{x}$ and $\bar{y}$ represents the average of observed and calculated quantiles respectively.

RMSE and MAE are widely reported as a measure for average model performance error (Willmott & Matsuura, 2005) and is the most commonly used scale-dependent measure especially in comparing estimation by different methods applied to the same set of data (Hyndman & Koehler, 2006). Even though RMSE is one of the most commonly used statistical error indices, it is not suitable to evaluate the fitness of the distribution function. In addition that both RRMSE and MAE perform better than RMSE, the evaluation of RMSE also relies on the scale of the dependent variable (Ahlburg, 1992). Hence, RMSE can only be used to compare forecasts from the same series across different models but not for comparing two different time series.

On the other hand, both Willmott & Matsuura (2005) and Hyndman & Koehler (2006) stated that MAE performed better than the RMSE. Willmott & Matsuura (2005) pointed out that due to the inconsistency of RMSE performance compared with MAE (for example RMSE tends to increase with MAE but not in a monotonic trend) and hence, MAE seems to be a better choice in measuring average error magnitude. Hyndman & Koehler (2006) on the other hand pointed out that RMSE is more sensitive to outliers compared with MAE.

Among the statistical error indices, Tao et al. (2002) found that the RRMSE is more suitable in the evaluation for heavily tailed data sets because it is less biased to outliers and offers a better picture of the overall fitting compared to RMSE.

Tao et al. (2002) used RMSE and MAE together with RRMSE as assessment tools besides the Q-Q plot and the Cunnane plotting formula is adopted to generate the empirical probability distribution based on the observed data. Both Zalina et al. (2002) and Deka et al. (2009) have implemented RASE, RMAE, PPCC and the L-moment ratio diagram along with the RRMSE as goodness-of-fit tests and using Gringorton plotting formula to denote the empirical distribution.

The PPCC method has been extensively used as assessment procedure by Kim et al. (2008), Zalina et al. (2002), Deka et al. (2009) after it was introduced by Filliben (1975) to calculate the correlation coefficient between observed and corresponding calculated quantiles for normality tests. The corresponding fitted quantiles are determined by the selected plotting position formula and Filliben (1975) recommended Blom's plotting formula to be used for the normal distribution according to the PPCC test. Filliben (1975) also mentioned that the PPCC test is also readily extendible as a distributional test statistic for non-normal hypothesis testing.

The PPCC test has been known as a powerful statistic for evaluating hypotheses distributions due to its simplicity in computation and its ability to provide a comparison of the results in terms of graphical form (probability plot) and also numerical form (correlation coefficient) (Vogel, 1986). Furthermore, the PPCC plot can be used as a fitting technique as it is able to estimate the shape parameter for distributions that only have one shape-parameter (Jaggi, 2003).

The application of PPCC is limited to distributions with two parameters (scale-parameter and location-parameter) and three parameters (scale-parameter, location-parameter and one shape-parameter) and hence it cannot be used for multi-parameter distribution such as Kappa and Wakeby distributions (Jaggi, 2003).

As the PPCC test is readily extendable for the use of non-normal distributions, more researchers have tried to use PPCC for fitting non-normal distributions such as the Gumbel population with the Gringorten's plotting position (Vogel, 1986). The Cunnane formula is used for several distributions which include EV1, GEV, LN3, P3 and LP3 distributions (Haktanir et al., 2010). Ideally, if the observed data fits the hypothesis distribution, the PPCC value will be close to 1.0 (Kim et al., 2010).

On the other hand, if the L-moments method is used for parameter estimation in the frequency analysis, then there are another two L-moments related statistics error indices namely the Z statistic and average weighted distance (AWD) that can be implemented especially when the L-moments ratio diagram is unable to determine the better candidate distribution for representing the sample data. The Z statistic measures the performance of the simulated L-skewness and L-kurtosis of the hypothesis distributon against the regional L-skewness and L-kurtosis from the sample data (Borujeni & Sulaiman, 2009).

The L-moments ratio diagram and Z statistic test have been applied in the precipitation frequency analysis in Texas (Asquith, 1998) and also in finding the best fitted distribution to represent annual maximum dry spell in Isfahan, Iran (Nasri & Moradi, 2011). As for the AWD, Yue & Wang (2004) have stated that it is proposed by Kroll & Vogel (2002) to evaluate the discrepancy of sample and hypothesis L-moments ratios.

2.1.4.4 Model discrimination methods

Bobée et al. (1993) showed that GOF tests such as χ^2 and KS tests have lower statistical power for envisaged alternatives. Hence, both the GOF tests and model discrimination methods such as Akaike information criterion (AIC) and, Bayesian information criterion (BIC) (also known as Schwarz information criterion) have to be applied especially in evaluation of multi-parameter distribution candidates with small sample size. Both AIC and BIC are used to identify suitable models for observed data but they have different approaches in model selection hence their model selection performance varies under different conditions. Mutua (1994) believed that the application of AIC reduced the inconsistency in flood frequency estimation compared to GOF tests such as chi-square and KS tests that have lower power especially for skewed distributions. Acquah (2010) found that the AIC method tends to find the best approximating model to an unknown data generating process while the BIC is used to detect the true model. However, Laio et al. (2009) commented that both the AIC and BIC shared some similarities where the basic of both methods is the log-likelihood function and it is useful in treating censored, truncated and binned data.

Acquah (2010) carried out a Monte-Carlo analysis to compare the performance of AIC and BIC for model selection in which the simulation result suggested that AIC performed better than BIC when the sample size is small ($n \leq 50$) but as the sample size increases, the performance of BIC improved with consistent performance while AIC performance is inconsistent.

Both Laio et al. (2009) and Acquah (2010) agreed that the BIC tends to choose a simpler model for instance two-parameter distributions instead of three or four-parameter distributions compared to AIC due to its parsimony characteristic. However Laio et al. (2009) adopted the AIC, BIC and AD in the peak discharges frequency analysis for catchments in the United Kingdom and found that the AD method is superior compared to model discrimination methods with lower effects of parsimonious in model selection.

Mutua (1994) applied AIC to identify the best distribution for flood frequency analysis and for identifying outliers in flood peak data for five river basins of Kenya. However, the application of model discrimination criteria for rainfall and flood frequency analysis is relatively rare and some researchers tend to combine model discrimination criteria with other goodness-of-fit test when assessing the fitness of hypothetical distribution functions. For example, Mohd. Deni et al. (2010) has applied the AIC and KS tests to identify the most suitable distribution function to represent dry and wet spells during the monsoon in Peninsular Malaysia. The application of the KS test indicated that four of 13 distribution functions tested are suitable to fit the dry spell data at 5% confidence level and the minimum AIC value revealed that the mixed log series with the truncated Poisson distribution is the best distribution function.

Laio et al. (2009) investigated the effectiveness of both AIC and BIC together with the AD test in identifying the best fitted distribution function for extreme hydrological variables but was unable to reach a conclusive result and, thus uncertain about the right model selection criterion.

2.14.5 Discussions

Graphical methods should be used as a tool for initial assessment as they are easier to construct and useful in outliers detection. However, when choosing between two or more fitted distributions and if these distributions gave relatively close estimations, then the graphical method is inappropriate in the selection of the best fit distribution. Hence, graphical methods are not the main assessment method in this study. It is very confusing to compare the results from the combination of five distributions and three-parameter estimation methods by visual judgement. According to Hosking & Wallis (1997), when more than one distribution is able to give adequate fit, then the best options will be the distribution that manages to give good quantile estimates even when the true physical process differs from estimation. Hence, statistical fit indices and conventional GOF tests are needed to obtain more precise results compared to the estimation among the selected hypotheses distribution functions. However, L-moments ratio diagram is adopted in this study to verify the fitness of the distributions identified for each region due to its ability to identify the parent distribution in regional frequency analysis.

Goodness-of-fit tests on the other hand have been found useful for the evaluation of candidate distributions to represent extreme hydrological events due to the emphasis on the upper tail of the distribution and hence, should be given more consideration on top of those assessment methods that measure the overall fitness of the distribution function. Also, as the data fitted with the candidate distribution function will then be extrapolated beyond the range of the data to estimate the probability of extreme events in frequency analysis, it is important to ensure the smallest estimation error at the upper tail which is relevant in examining the impact of climate change on extreme rainfall events. Furthermore, the GOF tests will be able to exclude the unsuitable distribution function based on the critical values at the required significance level.

Furthermore there is no specific rule for selecting one distribution over another and therefore, it remains unclear which criterion should be adopted for practical hydrology applications. Thus, Shabri & Jemain (2006) and Laio et al. (2009) agreed that more than one assessment method should be used during evaluation to reduce the element of subjectivity in choosing the statistical distributions. Bobee et al. (1993) also stated that by combining different GOF tests and model discrimination methods, the researcher will be able to obtain a better indication of a better fit distribution. Hence, more than one assessment method will be adopted in the process of reviewing the best fitted distribution in this study.

2.2 STATISTICAL TREND ANALYSIS

Rainfall patterns are becoming more unpredictable as a result of climate change (Rimi et al., 2009; Dejene et al., 2011). The detection of past changes or trends on rainfall characteristics due to climate change should be quantified by trend analysis using observed rainfall data and should be incorporated in design guidelines and standards (Madsen et al., 2014). In view of the changes in rainfall patterns for different regions, various studies have been carried out to investigate the temporal and spatial changes in rainfall pattern. With regard to the Asian context, trend studies have been carried out in China (Zhang et al., 2012), India (Goswami et al., 2006; Pal & Al-Tabbaa, 2009), Bangladesh (Shahid, 2011), Iran (Zarenistanak et al., 2014) and Southeast Asia region (Manton et al., 2001; Chang, 2011). In the trend studies, the upward trend signifies that the study area receives more rainfall and vice versa (Manton et al., 2001; Suhaila et al., 2010).

Zhang et al. (2012) examined both the temporal and spatial characteristics of precipitation in China and affirmed that precipitation has declined during spring and autumn but increases during the winter season. As for the spatial pattern, they found that the northern region of China is prone to the threat of drought while the eastern and southeastern parts are exposed to the risk of flood. While in India, rainfall trend analyses have been carried out on larger spatial scales that cover the whole central region and also smaller regional scales which only consist of southwestern India. Goswami et al. (2006) investigated the temporal change of extreme rainfall in the central region in India (within the longitude of 74.5°E to 86.5°E and latitude 16.5°N to 26.5°N) and found that the magnitude and frequency of extreme rainfall events (≥100mm rainfall/day) have increased but detected a decreasing trend for frequency of moderate rainfall events (5–100mm rainfall/day) during the monsoon season. As Pal & Al-Tabbaa (2009) focused on a smaller region which is Kerala (Southwestern of India), and noticed the temporal rainfall pattern has shifted. They found that Kerala has experienced more extreme rainfall during winter and autumn which increases the flood occurrence but has a significantly decreasing trend in spring. The results of these studies show that there is no spatially- and temporally-consistent pattern of rainfall trends throughout the study areas.

It is also found that the trend test results are affected by the sampling period. Manton et al. (2001) reviewed that the occurrences of extreme rainfall events have decreased in the Southeast Asia regions with 1961-1998 data. However, this is in contradiction with the Chang (2011) study which suggests that the frequency of extreme events has risen when using 1978-2007 data.

In recent years, a number of researches have been carried out to study the trends in Malaysia. Wong et al. (2009) studied the spatial and temporal rainfall trend with rainfall data from 1971-2006 for mostly the central region in Peninsular Malaysia. Suhaila et al. (2010) repeated a similar study that covers the entire Peninsular Malaysia and concluded that significant increasing trends have been observed in the total seasonal rainfall, frequency of wet days and rainfall intensities during the northeast monsoon. Whereas during the southwest monsoon, decreasing trends have been detected in the frequency of wet days for all stations over eastern, western and northwestern parts of Peninsular Malaysia but significant decreasing trends are only found in the northwestern region.

The following discussed how trend tests are used to quantify the changes in hydrological events over a certain period of time and also on how to identify the point of change where the properties of a time series changes with specific confidence levels.

2.2.1 Trend Tests

The impact of climate change on extreme rainfall and hydrologic frequency characteristics should be quantified and incorporated in design guidelines and standards by detection and attribution of past changes or trends. A trend is a pattern of change over time of a series of data in a certain direction, detectable by statistical parametric and non-parametric procedures. Madsen et al. (2014) summarised methodologies applied for trend analysis on extreme rainfall and flood due to climate change in Europe based on observation and future climate projections. There are a number of methods available to examine if significant trends exist in the data series such as linear regression test, Spearman's rho test and Mann-Kendall (MK) test.

The parameteric student t-test is based on linear regression, and therefore checks only for a linear trend. In addition, the t-test is less flexible as it requires the recorded data to be normally distributed. On the other hand, there is no such restriction for the MK test. The MK test is the most commonly used evaluation method in the literature especially for hydro-climatic variables (Diermanse et al., 2010; Novotny & Stefan, 2007; Mondal et al., 2012). The MK test (Mann, 1945; Kendall, 1975; Gilbert, 1987) assesses if there is a monotonic upward or downward trend of the variable over time.

Onoz & Bayazit (2003) remarked that the parametric test, t-test has less power compared to the non-parametric method, MK test when the probability distribution is skewed. Additionally, Yue & Pilon (2004) found that the power of trend tests are sensitive towards the shape of distributions, and the MK test has higher power compared to the t-test for asymmetrical distributions. Furthermore, the non-parametric tests are more robust as they require no assumptions about the distribution of the data and they are not sensitive to abrupt breaks due to inhomogeneous time series (Whitley & Ball, 2002; Jaagus, 2006).

The Spearman's rho test or Spearman's Rank Correlation Coefficient is another rank-based non-parametric test used to detect the presence of a monotonic trend within a given time series. Yue et al. (2002) showed that Spearman's rho test provides results almost identical to those obtained from the MK test and both tests are sensitive to the probability distribution type as well as the statistical properties of the sample data.

Stationarity of the sample is confirmed by a lack of sudden or large changes that occur during a sampling period. This change can be easily identified by the mean of the subsamples before and after the previously mentioned change. Numerous studies investigated the non-stationary availability in hydro-meteorological time series and subsequently attribute this feature as evidence of climate change. For instance, Milly et al. (2008) suggested that non-stationarity is unavoidable due to the substantial anthropogenic change in climate that altered the means and extremes of hydro-meteorological data such as precipitation, evapotranspiration, and discharge of rivers. Furthermore, the hydrologist is always aware of the presence of non-stationarity in water-related analysis and the limitations associated with assuming stationarity (Lins & Cohn, 2011).

Some of the statistical tests examine the stationarity of data series by splitting the series into two sub-series and tests if the two sub-series came from same distribution. In this study, two non-parametric tests have been applied, namely Mann-Whitney (MW) and, Mood's median tests. These two non-stationary tests are selected because they are commonly used for testing stationarity of hydrologic time series (Machiwal & Jha, 2008; Jakob et al., 2011; Osburn, 2011). The MW evaluates the significance of difference of the rank sums between two sub-series with critical values, which will be able to identify if the data are considered stationary (Kiely, 1999). While the median test compares the number of recorded data that exceed and are below the median for each sub-series (Zhang & Burn, 2009). In addition, the two sub-sets need not to have identical lengths (Mann & Whitney, 1947).

Both tests are unrestricted to any normality assumption regarding the distribution of the sampled time series. For the MW test, sample populations should have similar shape distributions although it is not a must for the median test (Osburn, 2011). The MW test has greater power especially when dealing with small samples (Freidlin & Gastwirth, 2000) but Mood's median test is more robust against the presence of outliers (Breyfogle, 2003). Overall, the MW seems more reliable as it is commonly used to check if the variables of a series come from same probability distribution (Haktanir & Citakoglu, 2014).

2.2.2 Change-Point Detection Test

A change-point is a point where the mean of the climate time series undergoes a structural pattern change. This change may or may not suggest there is a discontinuity in mean series values, but it indicates some pattern change for instance a shift in the time series trend slopes or the location parameters of the series (Lund & Reeves, 2002). The change point detection test is able to identify the point of change according to a specific confidence level in addition to identifying the presence of significance trends in the data series.

Numerous studies and reviews have been published on change-point detection methods which mainly focus on the detection and correction of non-climatic signals in time series (Peterson, et al., 1998; Reeves et al., 2007; Venema et al., 2012). However, this study focuses on the methods used for detecting the point where the time series changes in the parameters of the distribution. There are a number of statistical tests use to detect the point at which properties of a time series change and the beginning of a significant trend, for example the sequential Mann-Kendall test (Gerstengarbe & Werner, 1999; Ye et al., 2013; Huang & Fan, 2013), CUSUM method (Rusz, 2012; Gallagher et al., 2013) and Pettitt's method (Kiely, 1999; Salarijazi et al., 2012).

The cumulative sum (CUSUM) test is designed to examine whether the means in two parts of a record are different for an unknown time of change. This method is simple as it detects the change without assuming any functional form of the time series (non-parametric). CUSUM method has been used to detect changes in precipitation data (Kampata et al., 2008; Chowdhury & Beecham, 2010; Chu et al., 2012). For instance, Chu et al. (2012) identified the change points in long term extreme precipitation data using CUSUM and assessed the changes of hydrologic design procedure while Shehadeh & Ananbeh (2013) used CUSUM to assess the impact of climate change on winter rainfall in Jordan.

Pettitt's method was developed by Pettitt (1979) and is a rank-based nonparametric statistical test that is useful in detecting change-points or a shift in the mean value of time series (Xie et al., 2014). Pettitt's method can be used to detect non-linear trends but is a single change-point scenario. This method has been widely adopted by researchers in hydro-climatic series (Tomozeiu et al., 2000; Ho & Yusof, 2012; Zarenistanak et al., 2014).

The sequential Mann–Kendall test is used to identify the approximate year when the significant trend begins (Zarenistanak et al., 2014) and is able to detect multiple change-points within a given time series. The SMK test has been widely adopted by many studies in temperature (Zarenistanak et al., 2014), rainfall (Brunetti et al., 2001; Mosmanna et al., 2004; Partal & Kahya, 2006) and discharge series (Pavlič & Brenčič, 2011). In the Malaysian context, Amirabadizadeh et al. (2014) used sequential Mann–Kendall test and found out that most of the trends in the annual and seasonal time series started in the year 2000 for one of the catchment areas in Selangor, Malaysia. The statistic used for this method has been explained by Mosmanna et al. (2004), Karpouzo et al. (2010) and many others. The following chapter gives details of these techniques.

2.3 STUDY OF CHANGE IN RAINFALL TRENDS AND DISTRIBUTIONS

The importance of the ability in handling hydrologic variables has increased in recent years. The effects of climate change have added complications and increased uncertainty in water resources especially when dealing with extreme hydrologic events. The changes in rainfall trends may refer to changes in parameters of the underlying distribution or the parameters of the model used to describe the time series experienced changes for instance the mean, variance, or trend as shown in Figure 2.1. It is important to study the changes in the mean of the observed rainfall data to ensure the accuracy of estimates in hydrological modelling and to provide meaningful information and statistical characteristics such as change of mean or variance (Beaulieu et al., 2012).

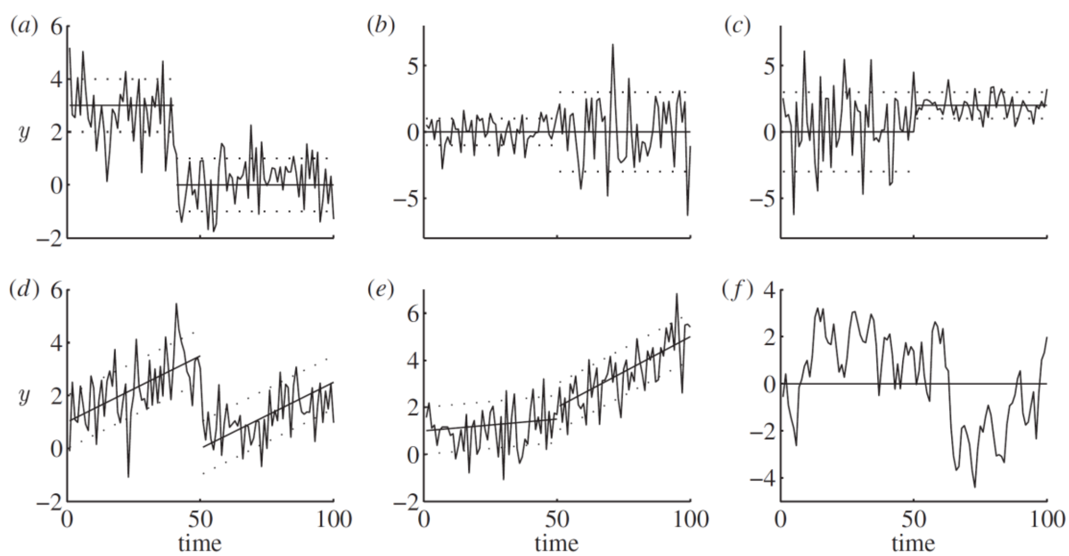

Figure 2.1: Examples of shifts in time series in (a) mean, (b) variance, (c) both mean and variance, (d) intercept of a linear regression pattern, (e) both intercept and trend of a linear regression pattern, and (f) no specific change point but with strong positive autocorrelation (Beaulieu et al., 2012)

According to Katz (1993), climate change may involve changes in both the location and scale parameters of the probability distribution of a climate variable. Some studies have been carried out to evaluate the change in the parameters of the distribution under the influence of climate change. Ben-Gai et al. (1998) analysed the annual rainfall distribution in Israel over a period of 60 years, covering two 30-year periods, thus revealing some significant spatial and temporal changes in the shape and scale parameter patterns of the fitted gamma distribution. Ben-Gai et al. (1998) propose that a strong increasing trend in the shape parameter and a decreasing trend of the scale parameter in the southern region of Israel suggested a decrease in aridity.

Cao et al. (2013) suggested kurtosis and skewness should be used to describe the distribution features of daily and extreme precipitation. Thus, research has been carried out to examined simulated and projected daily rainfall from the high-resolution regional climate model (COSMO-Climate Limited-area Modelling, CCLM) during 1961-2000 and 2011-2050 using the Mann-Kendall test to detect trends in the kurtosis and skewness of daily precipitation time series. Cao et al. (2013) found that in some parts of the Jianghuai region, central-eastern Northeast China and Inner Mongolia, the kurtosis and skewness will increase significantly, and precipitation extremes will increase in the future.

The changes in the aforementioned parameters have some important implications regarding the critical values at the upper tails of the distributions, and, consequently, the frequency of extreme rainfall events Ben-Gai et al. (1998). The changes in variability, skewness or shape of the distribution thus reflect a shift in the distribution of the variable that results in the increase or decrease in the probability of occurrences for an extreme climatic variable. The frequency of a climatic variable, for instance, temperature or mean annual rainfall depth, can be described by a probability distribution function. To evaluate the changes in frequency and also the intensity of the climatic events, we can compare the quantile estimated by the best fitted probability distribution function by previous recorded data and more recent recorded data. Hence, plenty of studies have been carried out by applying statistical procedures to model the extreme rainfall and flood flow data (Naveau et al., 2005). However, there has been limited research on the comparison and analysis of the distributions of extreme rainfall time series sampled from different sub-periods. In hydrologic analysis, it is conventional to assume hydrologic events are not affected by climatic trends or cycles and by furthermore assuming climatic time invariance when conducting conventional frequency analysis (Interagency Advisory Committee on Water Data, 1982; Rajagopalan et al., 2010).

The uncertainties in extreme precipitation events associated with the anticipated climate change and the inherent uncertainties related to the statistical frequency analysis of extreme precipitation events will be investigated. There are a few studies that take into account the climatic invariance and compare distributions of two sub-periods or based on a moving window approach in which the distributions are analysed within each time window. For example, Madsen et al. (2009) compared the regional model for estimation of extreme rainfall series in Denmark for shorter recorded periods 1979-1997 and longer periods 1979-2006.

Ntegeka & Willems (2008) assessed the estimated rainfall quantiles based on full series and five, 10 and 15 years moving windows in Uccle, Belgium.

CHAPTER 3: METHODOLOGY

This chapter outlines the methodology used for assessing the hydrologic statistics employed in the handling of rainfall trend and frequency analysis, while accounting for impacts from climate change. This chapter consists of two sections. Section 3.1 presents the statistical analyses adopted in this study. The brief overview of the methodology is as shown in Figure 3.1. Section 3.2 provides the background on the study area and selection of the recorded rainfall data used in this study.

3.1 INTRODUCTION

Several statistical tests are applied to assess spatial and temporal changes in rainfall patterns across Peninsular Malaysia. The following is an overview of the statistical methodology involved:

i. To examine if there is one distribution function that is able to give an adequate fit to

   a. all observed rainfall across the study area;

   b. all rainfall duration from one rainfall station

   using the entire record length of annual maximum rainfall series with eight different durations.

ii. To detect the changes in rainfall trend by applying the Mann-Kendall trend test. Different types of rainfall data such as annual rainfall, seasonal rainfall, inter-monsoon season rainfall and annual maximum series are used to examine the spatial and temporal variation of the trends.

iii. To identify the trend change-point by

   a. Non-stationary tests

   b. Sequential Mann-Kendall test

   using annual rainfall and annual maximum rainfall series.

iv. To identify the most suitable distribution function that can give an adequate fit to the annual maximum rainfall for each delineated region while further incorporating the impact of climate change using prior and posterior sub-series. The results are used for comparison with the analysis obtained from full series data.

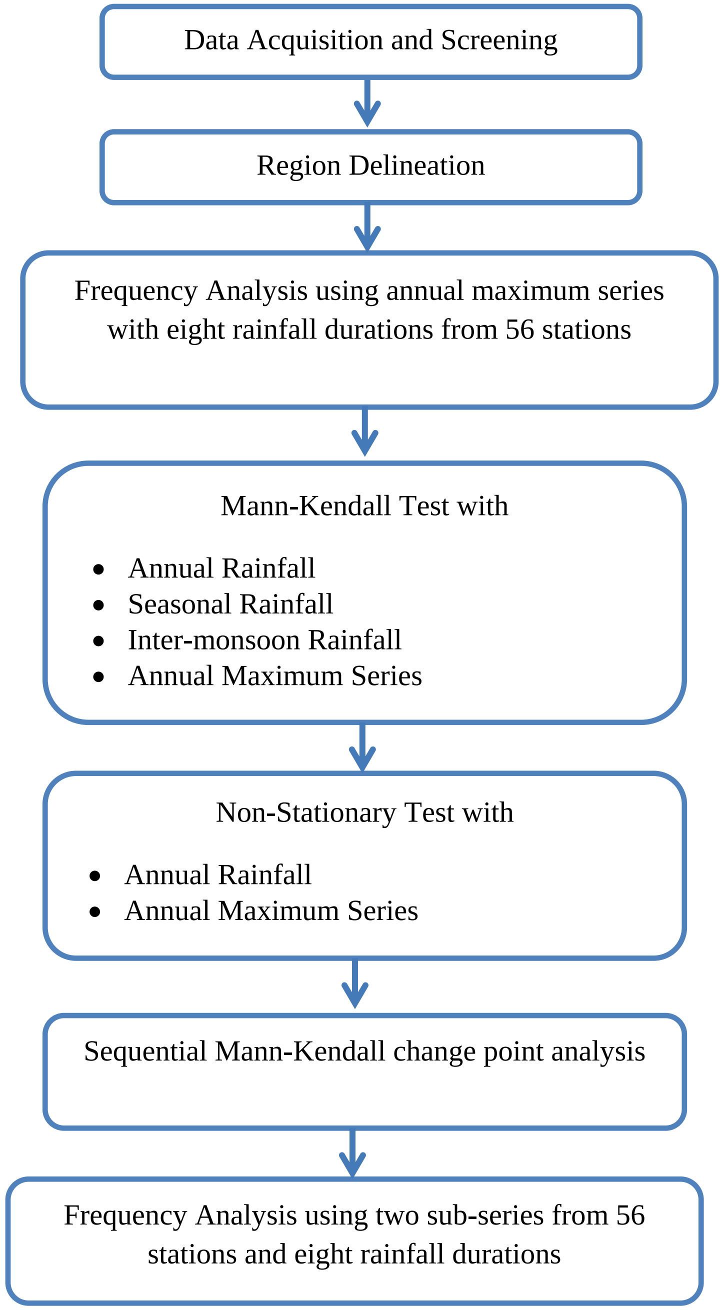

Figure 3.1: Overall methodology flowchart

3.1.1 Hydrologic frequency analysis using entire record length

Numerous hydrologic frequency analyses have been carried out to determine the best fitted probability distribution function and best parameter estimation method to represent the rainfall data (Park et al., 2000; Zalina et al., 2002; Nadarajah & Choi, 2007). It is common practice to consider various probability distributions, parameter estimation methods and plotting position formulas in fitting the observed rainfall data (either annual maximum or partial duration series) and the selection of best fitted distribution are based on quantitative assessment criteria.

The purpose of frequency analysis is to determine the best combination of probability distribution function and parameter estimation method to represent rainfall for the catchment area of interest. Statistical analyses were performed on the annual maximum rainfall series with eight different durations (refer to Section 3.1.2) to examine the rainfall events in short- and long-duration for all the rainfall stations. Furthermore, the results for this analysis are used for trends comparison against results obtained via analysis based on different sub-series (Section 3.1.5).

The following sections describe the choices of the probability distributions, parameter estimation methods, plotting position formulas and assessment procedures together with the justification for the selection.

3.1.1.1 Probability distribution functions

Five probability distribution functions are chosen as candidate distributions in this study. These five probability distribution functions are two-parameter Gumbel

(EV1) and lognormal (LN2), and the three-parameter generalised extreme value (GEV), lognormal (LN3) and log Pearson (LP3). These distributions are selected because they are commonly used in hydrologic frequency analysis to represent extreme hydrological events. The estimation of quantiles (x_T) corresponding to the required return period are computed based on the inverse distribution function. Refer to APPENDIX 2 for the formulas.

3.1.1.2 Parameter estimation methods

Method of moments (MOM), maximum likelihood method (MLM), and L-moments (LM) have been chosen in this study due to their popularity for estimating the hydrologic frequency parameters (Rao & Hamed, 2000; Engeland et al., 2004).

3.1.1.3 Plotting position formulas

A plotting position formula is applied as an empirical distribution for the recorded rainfall data in sample, which are then subsequently compared with the five selected distributions in order to verify whether they fit sample data. As different plotting positions interpret data differently, the choice of plotting position will affect the judgment of the fit to candidate distributions and hence, necessitate the selection of a different theoretical distribution.

3.1.1.4 Assessment procedures

A set of assessment procedures has been used to select the best fitted combination of probability distribution function and parameter estimation method. Two categories of assessment criteria, namely, Goodness-of-fit (GOF) test and statistical error indices were applied in this research. The GOF includes Kolmogorov-Smirnoff (KS) and, Anderson-Darling (AD) tests while statistical error indices include root mean square error (RMSE) and, Maximum Absolute Percent Error (MaxAPE). The flow of the assessment process is as shown in Figure 3.2.

The hypothetical distribution functions are tested using KS test with 10% significance level. GOF tests are used to evaluate the suitability of the candidate distribution according to a specific significance level, without relying on the plotting position formula.

Statistical error indices are less descriptive in rejecting or evaluating the hypothesis distribution and hence, inherit the element of subjectivity. This is because statistical error indices only evaluate how well the candidate distributions can imitate the empirical distribution without providing evidence in rejecting or retaining a hypothesis distribution. Lower values of RMSE and MaxAPE indicate a better fit of the model. In this case, the candidate distributions must first pass the GOF tests before being assessed by the statistical error indices. An “adequate fit” is obtained when a given candidate distribution passes the GOF test and has the requisite low value of RMSE and/or MaxAPE as depicted in the flowchart shown in Figure 3.2.

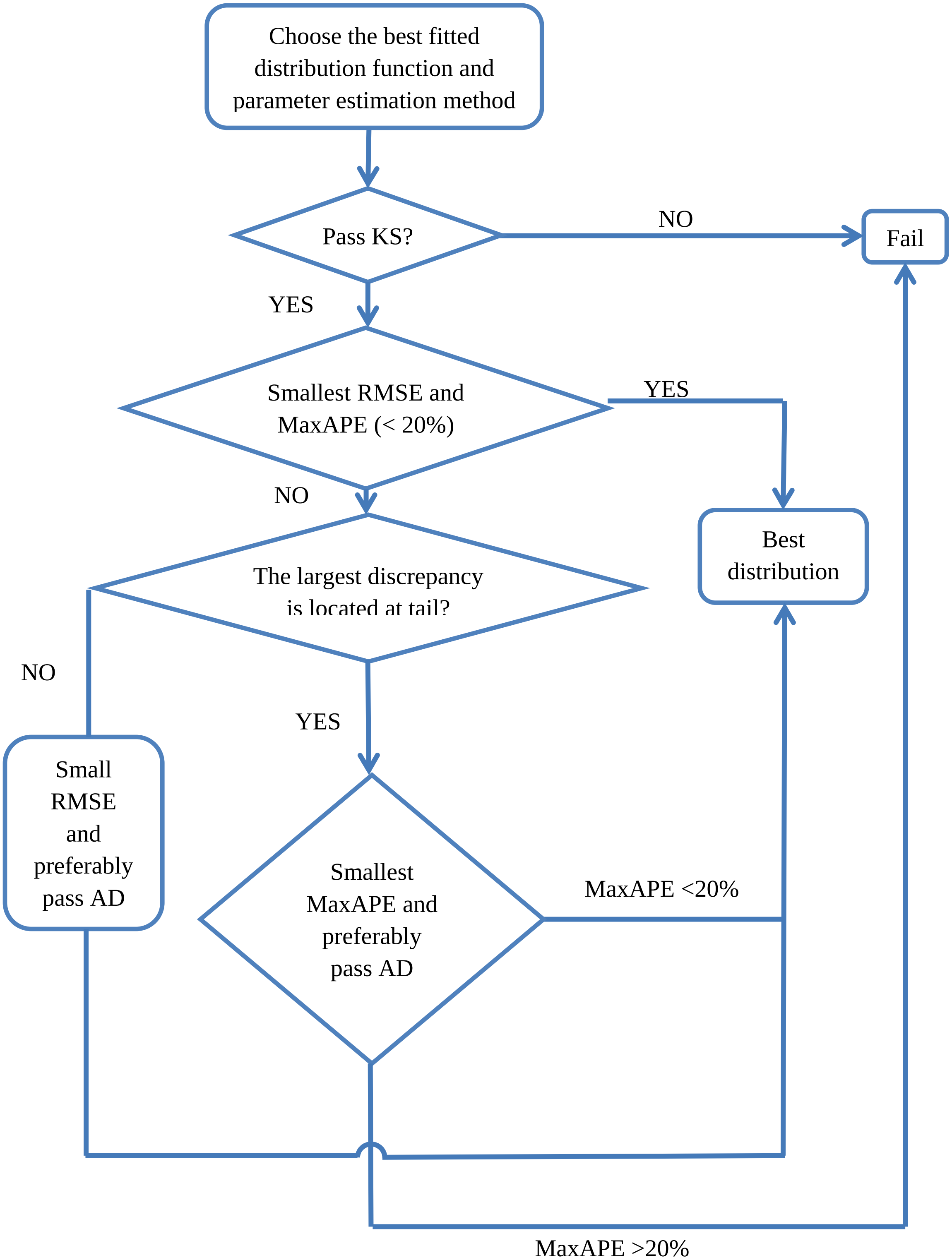

Figure 3.2: Flowchart of assessment procedure for frequency analysis

This study emphasises on the estimation of the extreme right-hand tail of a distribution, hence the position of the largest discrepancy (i.e. the divergence between empirical and candidate distributions) found is most important. If more than one candidate distribution has the largest discrepancy found at the right tail section, then the candidate distribution with smallest MaxAPE value will be chosen. However, if the theoretical distribution diverges from the empirical distribution for more than 20% at the right tail section, then the distribution will be considered as "failed" in fitting the rainfall data. For model evaluation, the simulation results can be considered as "fair" when the absolute error range is between 15 to 25 percent (Singh et al., 2004; Moriasi et al., 2007).

On the other hand, when the largest discrepancy is not detected at the right tail section of the candidate distributions, then the distribution with smallest RMSE value will be chosen.

3.1.2 Mann-Kendall trend test

The purpose of the MK trend test is to identify the changes in trend for rainfall pattern within the data time series and their spatial variation for all the stations. The test statistic, Kendall's S is defined as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \left(x_j - x_k\right) \tag{1}$$

where n is the sample size while x_j and x_k are the serial data. When the size of the sample is greater than 10, Kendall's S will be approximated as normally distributed with a correction for ties when $x_j = x_k$. The computation of mean and variance of S is provided as follows:

$$E(S) = 0 \tag{2}$$

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_p^q t_p\left(t_p - 1\right)\left(2t_p + 5\right)}{18} \tag{3}$$

where q is the number of tied group and t_p is the occurrence of the tie number within the tied group. Then S and Var(S) are used for the computation of the test statistic, Z as follows:

$$Z_c \begin{cases} \dfrac{S-1}{[Var(s)]^{0.5}} & ,if\ S > 0 \\ 0 & ,if\ S = 0 \\ \dfrac{S+1}{[Var(s)]^{0.5}} & ,if\ S < 0 \end{cases} \tag{4}$$

The value of Z_c is used as a measure of significance of trend. If $|Z_c|$ is greater than the critical value of a chosen significance level in a two-tailed test then the null hypothesis is rejected. A positive Z_c value indicates an upward trend while negative implies a downward trend.

Trends in historical hydrologic data are determined based on the p-value and the chosen significance level. Significance levels of 0.05 and 0.10 were applied to evaluate the reliability of the identified trend. Following the suggestions from the IPCC (2007), these confidence levels are categorized as:

i. 0.05 significance level is categorised as “extremely likely”

ii. 0.10 significance level is categorised as “very likely”

It is common to choose 0.05 and 0.10 significance levels in frequency analysis studies.

3.1.3 Non-stationary tests

Non-stationary tests can be used for trend analysis by dividing the time series into two halves and by examining the null hypothesis if the two sub-series are from the same population. There are several statistical tests available for examining the stationarity of rainfall time series. In this study, two non-parametric tests have been applied, namely Mann-Whitney and, Mood’s median tests. Both non-stationary tests are applied in order to cross check the analysis result.

The purpose of non-stationary tests are to assess the statistical significance of changes in annual rainfall and annual maximum rainfall from an earlier to a later period (all the available data before year 1994 and from 1995 to 2011) for the eight rainfall durations at a 10% significance level.

All rainfall data were obtained from rainfall stations with more than 30 years of records. Among these rainfall series, most of the rainfall stations (more than 46%) have record lengths ranging from 36 to 40 years. The year 1995 is fixed as the cutting point. The purpose of this study is not to determine the exact year where the change developed but only to determine the change within a reasonable range using trend analysis. Although it is difficult to divide all the time series into halves by a single year since the record range differs from one data to the next, a single year has been chosen to maintain consistency in the analysis. In this case, year 1995 was selected, in line with the Malaysian Meteorological Department data, where a positive change can be detected (Malaysian Meteorological Department , 2015).

Mood's median test examines the equality of medians from two or more sub-series with the minimum sample size of 10 for each sub-series. The median test calculates the number of observations per sub-series less than or equal to the overall median and greater than the overall median. The expected values are then calculated and the chi-square procedure is used as significance tests.

As for the Mann-Whitney test, the method of computation can be summarised as follows:

1. Separate the time-series into two sub-series:
   (i) prior (n_1) up to and including year 1994
   (ii) posterior (n_2) from year 1995 onward
2. The magnitudes of x_j rainfall series (j=1,…,n) are ranked regardless which sub-series they belong to.
3. Sum the ranks (T_1 and T_2) for each sub-series and identify the sub-series with larger sum of ranks.
4. Determine the test statistic, U as follows:

$$U = n_1 n_2 + \frac{n_x(n_x+1)}{2} - T_x \qquad (5)$$

   Where T_x is the larger rank summation and n_x is the corresponding sample size.

5. When the sample size (n_1 or n_2) is greater than eight, the test statistic can be approximated by the normal distribution as:

$$z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} \tag{6}$$

The significance level for both non-stationary tests is set at 0.10 to determine the stationarity of the time-series.

3.1.4 Sequential Mann-Kendall (SMK) change-point analysis

The SMK test (also known as Mann–Kendall Rank Correlation test) is proposed by Sneyers (1990 cited Karpouzo et al., 2010) and recommended by the World Meteorological Organization (WMO) (Mohsin, 2009).

The SMK test was carried out to identify the beginning of a significant trend (if there is any significant trend detected) within the rainfall series. The identified change-points will then be compared with the fixed cutting point from the non-stationary tests to check whether the results from both sections are coherent.

In this case, the SMK test detects the distributional changes within a sample by estimating the likelihood that a change occurred and by identifying the point of change at a specific confidence level. This test consists of two series, a progressive series u(t) and a backward series u'(t). When these two series intersect and continue to propagate beyond a specific significance level, the intersection marks the beginning of the statistically significant trend.

The following steps are applied to test the hypotheses:

1. The magnitudes of x_j rainfall series (j=1,…,n) are compared with x_k (k=1,…,j-1). At each comparison, the number of cases $x_j > x_k$ is counted and denoted by n_j.
2. The trend statistic, t is computed as follows:

$$t_j = \sum_{1}^{j} n_j \qquad (7)$$

3. The distribution of t, under the null hypothesis, is practically a normal distribution with the mean and variance given by the following expressions:

$$e(t_j) = \frac{j(j-1)}{4} \qquad (8)$$

$$Var(t_j) = \frac{j(j-1)(2n+5)}{72} \qquad (9)$$

4. The sequential values of statistic u are then calculated as:

$$u(t_j) = \frac{t_j - e_{(t_j)}}{\sqrt{var(t_j)}} \qquad (10)$$

Similarly, the values of u'(t) are computed backward, starting from the end of series. The intersection of the curves showing the u(t) and u'(t) represents the time of change or the start of a new trend. Significance levels of 0.05 and 0.10 were applied to evaluate the reliability of the identified trend and change-point.

3.1.5 Hydrologic frequency analysis using sub-series

Several studies have been carried out to assess the temporal trends in annual maximum rainfall series with two phases of data (Madsen et al., 2009; Chu et al., 2013). This is because the distribution of extreme rainfall could have been altered or the shape of the distribution function might have changed due to the changes in rainfall patterns.

In this study, hydrologic frequency analysis was carried out to assess changes in the distribution of annual maximum rainfall series using both prior and posterior sub-series. The quantiles derived from each sub-series are compared among each other, and with the quantiles estimated using the full series (for the given return periods).

The purpose of frequency analysis using sub-series data is to determine the best combination of distribution function and parameter estimation method in fitting each sub-series data and to evaluate the distribution of rainfall series from different sub-series under the influence of changes in rainfall pattern.

Overall, the application of the hydrologic frequency analysis in this section is a follow up to the analyses carried out in **Section 3.3.1**. In this case, the full series data is divided into two sub-series with year 1995 as the change-point to compare the changes and assess the distributions of annual maximum rainfall from different series. As aforementioned in **Chapter 1**, it is reasonable to select year 1995 as a point of reference for the beginning of a significant warming trend and the warming phenomenon is further enhanced with the 1997-1998 El Niño event which stands out as an extreme event (Houghton et al., 2001). As the warmer temperature encourages the evaporation of water from land and sea and allows the atmosphere to hold more moisture, this increases the possibility of that more extreme precipitation will happen (Trenberth, 2010).

The data has been divided at year 1995 to produce two sets of data for a station. As a result, this typically leads to shorter data series for each station ranging from 1971/1982 – 2011, and this may impact the reliability of outcomes from the analyses. The accuracy of the results could be improved by increasing the number of years of data (Lee, 2005). Hence, there is a need to carry out the analysis in order to project what will happen in the near future and the accuracy of estimation can be improved later when more data is available.

The estimated quantiles derived from both sub-series are compared with the estimated quantiles obtained from full series data for 100-years return periods. It is common practice to use 100-years return period as a level of protection for designing major water resources or hydraulic structures in Malaysia (National Hydraulic Research Institute of Malaysia, 2010). The purpose of this study is not to generate accurate 100 year rainfall but to look into analysing the rainfall differently due to climate change, while the estimated quantiles for 100-years return period are only used to form a basis for comparison. In addition, extreme rainfall of 100-years is just a statistical estimation for engineering analysis and design and cannot guarantee 100% accuracy. Hence, the practical issue is how to select a reasonable probability distribution to describe the rainfall events, so that the engineer can make reliable quantile estimates.

From the results of frequency analysis using sub-series, the best fitted combination of probability distribution function and parameter estimation method for all the stations are presented based on the delineated regions. Then, the selection of the regional distribution is carried based on the L-moment ratio diagrams in each region to validate the competence of potential distribution functions. In addition, the results also examine the rainfall distribution in short- and long-durations for each delineated region. Rainfall that lasted less than three hours are categorised as shorter duration rainfall, while for rainfall that lasted for more than three hours are classified as long duration rainfall.

3.2 STUDY AREA AND DATA COLLECTION

3.2.1 Study Area

Peninsular Malaysia is located within the latitude of 1˚15’ N to 6˚45’ N and longitude of 99˚20’ E to 104˚20’ N covering an area of 131 587 km^2 (Figure 3.3). The climatic conditions of Peninsular Malaysia are uniformly warm throughout the year with temperatures ranging from 21°C to 32°C and characterized as humid with high average annual rainfall of over 2000 mm.

Figure 3.3: Map of Malaysia (U.S. Central Intelligence Agency, 1998)

In general, the rainfall pattern of Peninsular Malaysia is under the influence of two monsoon seasons, which are the southwest monsoon from May to September and northeast monsoon from November to March. The transition periods between two monsoons, in the months of April and October are known as inter-monsoon periods.

The Titiwangsa Range extending 480 km from the border of Thailand to the state of Negeri Sembilan divides the peninsula into the east and west coasts. This division has an effect on the spatial variation of the monsoon seasons. For instance, the east coast of Peninsular Malaysia comprising the states of Kelantan, Terengganu, Pahang and the east coast of Johor are affected by northeast monsoon that brings heavy rainfall. The west coast of Peninsular Malaysia on the other hand is affected by the more subtle and relatively drier southwest monsoon but will receive heavy convective rainfall along with thunderstorms during the inter-monsoon period.

3.1.2 Data Collection

Several types of rainfall data from 127 rainfall stations in Peninsular Malaysia have been obtained from the Department of Irrigation and Drainage Malaysia (DID). These rainfall data include annual maximum series, as well as total monthly and annual rainfall data. The total monthly rainfall from November to March signifies the Northeast Monsoon rainfall; while May to September represents the Southwest Monsoon rainfall; and the respective months of April and October represent the Inter-monsoon rainfall.

In addition, the annual maximum rainfall data with eight durations were collected to assess the patterns of rainfall using frequency analysis while the total monthly and annual rainfall data are used to evaluate changes in rainfall trends. According to the National Hydraulic Research Institute of Malaysia (2010), storm duration data with an interval of 15-minute, 30-minute, 60-minute, 3-hour, 6-hour, 12-hour, 24-hour, 3-day, 5-day and 7-day are recommended for the derivation of design rainstorm. However, the estimates of Probable Maximum Precipitation (PMP) of one and three-day storm durations for longer duration rainfall are often adopted in Malaysia (National Hydraulic Research Institute of Malaysia, 2008). Hence, the annual maximum for eight rainfall durations as shown below were obtained and categorised into short- and long-duration rainfall. As suggested by Hydrometeorological Advisory Service (2003), the rainfall duration up to three hours for catchment over areas up to 1000 km^2 are considered as short duration rainfall.

Rainfall Duration	
15-minute	Short-duration Rainfall
30-minute	
1-hour	
3-hour	
6-hour	Long-duration Rainfall
12-hour	
24-hour	
72-hour	

The rainfall data from these 127 stations all have minimum record length of 20 years but vary in the length of data gaps. Data screening was conducted to identify rainfall stations used in this study. In view of the natural variability in climate system that will persist for multi-years, decades or even longer for the study of climate change, data with a minimum record length of 25 years (Burn & Elnur, 2002) are needed to ensure the statistical validity of the trends obtained. Based on the recommendation by Burn & Elnur (2002) and Fleig et al. (2013), the criteria for the selection of stations in this study was based on both the length of data availability, and the completeness of recorded rainfall data.

Accordingly, only rainfall stations with a minimum of 30 years of records and no missing data for more than six consecutive months (Miller & Frederick, 1969) will be used in the study. After the data screening, 56 rainfall stations fulfill the aforementioned criteria. Table 3.1 shows the distribution of these 56 rainfall stations within various states in Peninsular Malaysia. Furthermore, no outlier tests were performed since all outliers are perceived as genuine but extreme events. This is consistent with the view that researchers should treat outliers as extreme events, see Orr et al. (1991) and Resnick (2007).

Table 3.1: Number of rainfall stations across Peninsular Malaysia

State/ Federal Territory	**Number of stations**
Johor	7
Kedah	5
Kuala Lumpur	6
Kelantan	2
Melaka	1
Negeri Sembilan	2
Perak	8
Perlis	1
Pahang	7
Penang	4
Selangor	8
Terengganu	5
Total	**56**

The length of the recorded rainfall data ranges between 30 to 41 years. The distribution of the stations according to record length is shown in Table 3.2. Refer to APPENDIX 3 for the details of records which include station number and location.

Table 3.2: Distribution of the rainfall stations according to record length

Record lengths (Years)	Number of stations
< 30	0
30-35	12
36-40	26
41	18
Total	**56**

These 56 rainfall stations are then classified into five regions namely northwest, central west, southwest, inland and east coast regions of Peninsular Malaysia. The delineation of the regions is mainly based on the physical characteristics (distance to the nearest coast, the different extents of the influence of the monsoon to the study area). See Figure 3.4 for the locations and distributions of these rainfall stations.

The delineation of the five regions was carried out by referring to the hydrological region demarcation in Peninsular Malaysia in Hydrological Procedure No. 5: Rational Method of Flood Estimation for Rural Catchments in Peninsular Malaysia (Department of Irrigation and Drainage Malaysia, 2010) and Technical Guideline for Estimating Probable Maximum Precipitation for Design Floods in Malaysia (National Hydraulic Research Institute of Malaysia, 2008). This was further revised based on the effect of:

i. a barrier such as a range of hills on the depletion of moisture supply to the storm (World Meteorological Organization, 1986)
ii. distances factor from the coast (World Meteorological Organization, 1986)

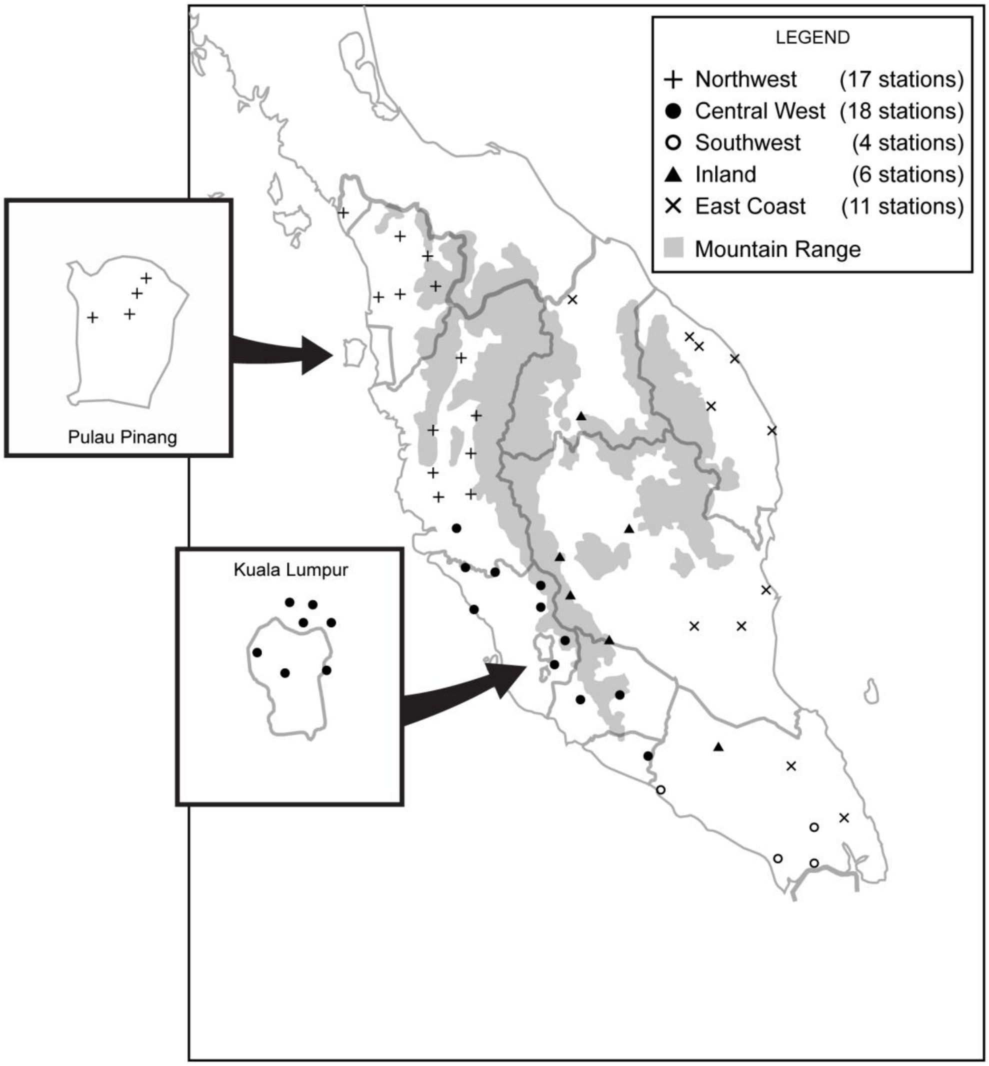

Figure 3.4: Location of rainfall stations according to the regions

CHAPTER 4: RESULTS AND DISCUSSIONS

This chapter presents an analysis of changes in rainfall trends across Peninsular Malaysia under the influence of climate change and how such trend changes affects statistical distribution fits obtained from observed rainfall data. This chapter demonstrates the handling of non-stationarity in rainfall series, identifies the trend change-point, and compares the results of frequency analysis with and without the trend change-point (the time at which the trend begins to change). It is expected that the inclusion of the trend change-point in the frequency analysis will increase or decrease the magnitude of estimated rainfall, and that this, in turn, will be reflected in the estimated quantiles which affects the design of hydraulic structures.

This chapter is organised into six sections. Section 4.1 presents the result of hydrologic frequency analysis when the full-series data (entire record length of data) is used. Section 4.2 presents the results of Mann-Kendall trend tests which were carried out to detect changes of trend in rainfall patterns as well as changes in their spatial and temporal correlation. The changes in rainfall pattern are described in terms of magnitude and intensity. Section 4.3 presents the outcome of the two non-stationary tests (Mann-Whitney and Mood's median test) and Sequential Mann-Kendall test used to determine the location of the trend change-point. Section 4.4 presents the outcomes of frequency analysis applied to the full-series data and both sub-series data (full series data divided into a prior and posterior sub-series at year 1995). Section 4.5 presents the summary of the main findings from this research. The conclusions of this chapter are in reported in section 4.6.

4.1 FREQUENCY ANALYSIS USING FULL SERIES DATA

The objective in this section is to determine if there is a specific distribution function that can give an adequate fit to (i) all stations across the study area and, (ii) all selected durations for a specific station. The criteria for obtaining an "adequate fit" are as previously described in Section 3.1.1.4. The outcomes from this section will form the control for a follow-up investigation in Section 4.4 focused on changes in distribution for annual maximum rainfall using different sub-series.

The summary of the frequency analysis results for 56 rainfall stations with eight rainfall durations are shown in Table 4.1. In this case, GEV distribution (regardless of the choice of parameter estimation methods implemented in this thesis) outperforms alternative distribution functions in fitting the annual maximum rainfall series for all durations considered.

Table 4.1: Results of the frequency analysis for 56 rainfall stations across study area with selected rainfall duration

Rainfall Duration	GEV	LP3	LN3	EV1	LN2	Fail
15-minute	22	1	7	2	2	22
30-minute	28	2	4	6	2	14
1-hour	32	3	4	5	2	10
3-hour	34	1	2	7	5	7
6-hour	26	2	4	9	9	6
12-hour	31	1	2	7	7	8
24-hour	26	1	7	4	10	8
72-hour	24	4	3	6	12	7

More than 39% (22 stations) to 61% (34 stations) of the rainfall data from each of the selected duration were best fitted by GEV. The result in Table 4.1 also shows that rainfall data from some stations i.e. 39% of 15-minute and 25% of 30-minute rainfall fail to be fitted by any of the candidate distribution functions. The goodness-of-fit (GOF) tests have rejected all the distribution functions for more than one-quarter of the short duration (15-minute and 30-minute) rainfalls. Overall, more than one candidate distribution functions are required to give adequate fit to data from all stations in this study.

There are two reasons where the rainfall data failed to be fitted by any of candidate distributions. Firstly, the rainfall series are poorly fitted when a significant trend is detected. According to Wilson et al. (2011), a poorly fitted distribution gives a poor representation of current and future rainfall frequencies. Hence, statistical tests (e.g. the Mann Kendall test) are used to determine whether the rainfall series displays a significant trend that may indicate the presence of non-stationarity.

Secondly, the presence of extreme data at the right tail causes 15-minute and 30-minute interval data to fail to be fitted by any of the candidate distribution functions. For example, the rainfall data from station 3216001 in Kuala Lumpur (central west region) demonstrates how the extreme rainfall data at the right tail (as shown in Figure 4.1) is particularly difficult to be fitted by the candidate distributions. Figure 4.1 shows the quantile-quantile (Q-Q) plot that compares the fit of the GEV distribution to the 15-minute observed AMS rainfall data. The amount of observed rainfall is on the vertical axis and the amount of estimated rainfall from the GEV distribution is on the horizontal axis. From the Q-Q plot, it shows that the GEV distribution allocates insufficient probability on the right tail, although in the lower part of the distribution the fit is quite close.

The appearance of extreme data cause distortion to the estimates of parameters and adds considerable difficulty in fitting the candidate distributions considered. In spite of this issue, it is not practical to remove such outliers since changes in the frequency of their occurrence or magnitude may provide signals for the presence of climate change (which manifests as non-stationarity in the data). According to Fisher (cited in Reiss & Thomas, 2007), the rejection of observations is too crude to be defended and unless there are other reasons for rejection than the mere divergences from the majority, it would be more logical to accept these extremes. In this sense, extreme rainfall data are not omitted during the construction of samples in this study since these can be subjected to statistical analyses that inform us of the significance of any observed pattern change.

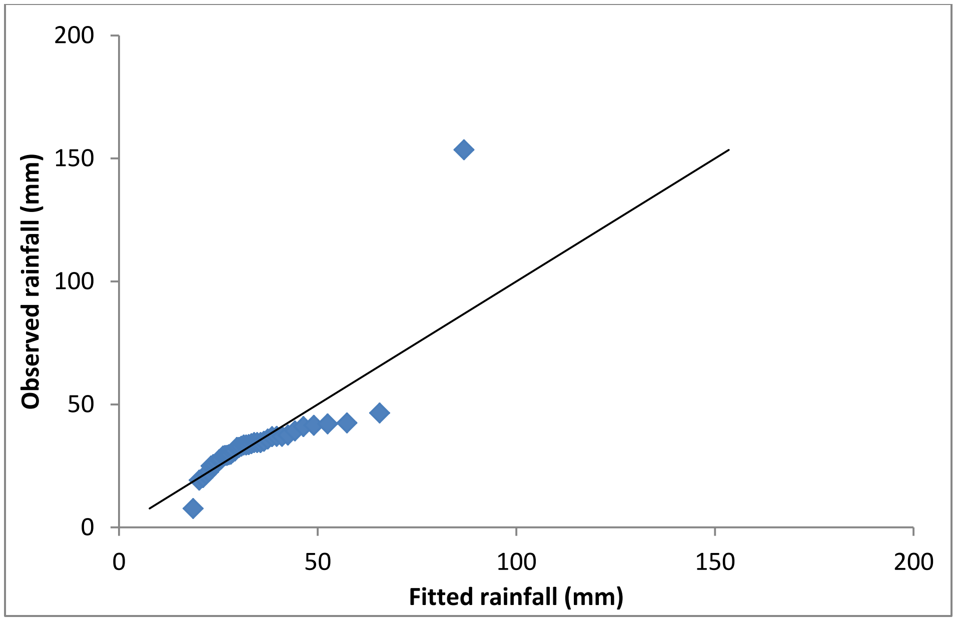

Figure 4.1: Q-Q plot showing the fit of GEV to the station 3216001

The aforementioned results describe the case for the entire study area without look into the details for each delineated region. However, Dore (2005) pointed out that rainfall pattern can undergo inconsistent temporal and spatial changes across different equatorial regions. Thus, it is important to examine the change of extreme rainfall for each delineated region on a case by case basis. We describe these results in the paragraphs that follow.

In the northwest region, rainfall series from 17 rainfall stations are examined and more than one distribution function was needed to fit the data from (i) different durations from the same rainfall station and (ii) data from all stations for a specific rainfall duration. The probability distributions that best fit the AMS data for eight durations from all stations in northwest region are shown in Table 4.2.

Table 4.2: Results of the frequency analysis for 17 rainfall stations across northwest region with selected rainfall duration

State	Station Number	GEV	LN3	LP3	EV1	LN2	Fail
Perlis	6401002	5	0	1	1	1	0
Kedah	5704055	4	2	0	0	2	0
	5806066	4	0	0	1	0	3
	5808001	5	1	0	1	1	0
	6108001	7	0	0	1	0	0
	6206035	6	1	0	0	1	0
Penang	5302001	3	1	0	0	4	0
	5302003	7	0	0	0	1	0
	5402001	3	0	1	2	0	2
	5402002	5	1	1	0	1	0
Perak	4209093	3	0	0	4	0	1
	4311001	6	0	0	1	0	1
	4409091	6	1	1	0	0	0
	4511111	5	0	0	0	0	3
	4708084	4	2	0	2	0	0
	4811075	7	0	0	1	0	0
	5210069	5	0	0	3	0	0

Table 4.3 shows the results of frequency analysis for 17 stations based on eight rainfall durations. The GEV distribution gave an adequate fit to most of the rainfall data (roughly 41% to 94%, varies with duration of rainfall). From the result of GOF tests, it is more difficult to fit the rainfall data based on short duration (15-minute and 30-minute) rainfall with higher percentage of the data (approximately 20%) failed to be fitted by any of the candidate distribution as some of these data have high skewness and kurtosis values. The skewness of 15-minute rainfall ranges from -0.245 to 4.971 and the kurtosis ranges from -0.988 to 26.088 while skewness of 30-minute rainfall is from -0.028 to 4.176 and the kurtosis varies between -0.943 to 21.942. According to Garson (2012), if the skewness is less than -2 or greater than 2 then the distribution is highly skewed

while the range of acceptable deviations for the kurtosis should be within the ±3 range.

More than one distribution function was needed to provide adequate fits to the majority of the stations for longer duration rainfalls such as 6-hour to 72-hour rainfall. For example, GEV and LN2 distributions fit most of the stations (around 70% of the data) for 72-hour rainfall. Meanwhile, for 12-hour and 24-hour rainfall, GEV is able to fit the majority of the data (i.e. 71% of the cases studied).

Table 4.3: Results of the frequency analysis across northwest region for eight rainfall durations

Distribution	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
GEV	10	10	11	16	7	12	12	7
LP3	1	0	0	0	1	0	0	2
LN3	1	1	1	1	1	0	3	1
EV1	1	2	3	0	6	3	2	1
LN2	0	1	0	0	2	2	0	5
Fail	4	3	2	0	0	0	0	1
Total	17	17	17	17	17	17	17	17

None of the data from three- to 24-hour rainfall data in the northwest region failed to be fitted by candidate distributions compared to other duration rainfalls. The skewness of 15-minute to one-hour rainfall ranges from -0.245 to 4.971 and the kurtosis ranges from -0.988 to 26.088, while for three-hour to 72-hour rainfall, the skewness value falls within the range of -0.295 to 2.455 and the kurtosis varies between -1.002 to 9.346. The sample skewness and kurtosis of three-hour to 72-hour rainfall data values in the northwest region are lower compared to sub-hourly rainfall which indicates that most of the three-hour to 72-hour rainfall have light tails or a lack of outliers (DeCarlo, 1997). The sample parameter values for all durations and regions are as listed in APPENDIX 7. Refer APPENDIX 7, some of the reported standard deviation, skewness and kurtosis values are high because of observations that have extremely large magnitude. Such instances are outliers (relative to what is expected from a normal distribution) with values typically larger then $Q_3 + 1.5 \times IQR$ (Tukey, 1977). Here, Q_3 is the third-quartile while IQR is the interquartile-range given by the difference between the third quartile with the first quartile, Q_1. The presence of outliers has a significant influence on the coefficient of skewness and kurtosis while both the mean and standard deviation are inflated by the presence of outlier observations.

Table 4.4 shows the analysis results for 18 stations in the central west region based on eight duration rainfall data. As can be seen, more data in the central west region fails to be fitted by any candidate distribution function. The results of the GOF tests revealed that 12 out of 18 stations experienced difficulty in finding the adequate distribution function to fit the data. Table 4.5 shows the number of data series that can be fitted by distribution functions corresponding to the rainfall durations considered.

Table 4.4: Results of the frequency analysis for 18 rainfall stations across central west region with selected rainfall duration

State	Station Number	GEV	LN3	LP3	EV1	LN2	Fail
Perak	4010001	4	0	0	1	0	3
Selangor	2917001	5	1	1	0	1	0
	3117070	3	0	0	2	2	1
	3118102	6	0	0	0	0	2
	3411017	3	1	0	1	2	1
	3416002	7	0	0	1	0	0
	3516022	3	0	1	2	1	1
	3613004	3	0	0	0	3	2
	3710006	2	3	0	1	1	1
Kuala Lumpur	3116003	3	1	0	0	1	3
	3116006	4	2	2	0	0	0
	3216001	5	0	0	1	0	2
	3217001	4	2	0	0	0	2
	3217002	2	0	0	1	1	4
	3217003	6	0	1	1	0	0
Negeri Sembilan	2719001	7	1	0	0	0	0
	2722002	4	0	0	0	1	3
Melaka	2224038	4	1	2	0	1	0

Similar to the northwest region, the rainfall data from shorter duration (15-minute and 30-minute) rainfalls are more difficult to be fitted by any of the candidate distributions since more than 20% (4 out of 18 stations for 30-minute rainfall is 22% and hence, more than 20%) of the data fail to be fitted, as shown in Table 4.5. Besides GEV, other distributions also provide an adequate fit for more than 20% of the stations for most of the rainfall durations.

Table 4.5: Results of the frequency analysis across the central west region for eight rainfall durations

Distribution	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
GEV	5	10	9	10	12	11	9	9
LP3	0	1	3	1	0	1	0	1
LN3	3	2	2	0	2	2	0	1
EV1	0	1	1	3	0	1	1	4
LN2	2	0	1	2	3	1	5	0
Fail	8	4	2	2	1	2	3	3
Total	18	18	18	18	18	18	18	18

The southwest region consists of four rainfall stations and Table 4.6 shows that the LP3 distribution is not suitable to fit the AMS series of any duration in the southwest region. Table 4.7 shows that GEV distribution is more robust in fitting most of the data except for 15-minute, three-hour and 24-hour rainfall in this region.

Table 4.6: Results of the frequency analysis for 4 rainfall stations across southwest region with selected rainfall duration

State	Station Number	GEV	LN3	LP3	EV1	LN2	Fail
Johor	1437116	4	1	0	1	0	2
	1534002	6	1	0	0	1	0
	1737001	2	1	0	1	0	4
	2025001	3	1	0	1	3	0

Table 4.7: Results of the frequency analysis across southwest region for eight rainfall durations

Distribution	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
GEV	1	3	3	0	2	3	1	2
LP3	0	0	0	0	0	0	0	0
LN3	1	0	0	1	0	0	2	0
EV1	0	0	0	0	1	1	0	1
LN2	0	0	0	2	1	0	0	1
Fail	2	1	1	1	0	0	1	0
Total	4	4	4	4	4	4	4	4

As can be seen in Table 4.8, both the LN3 and LP3 distributions are not suitable to fit data in the inland region. The GEV and EV1 distributions are able to represent the data for most of the stations; 60.4% of the data (from all durations) can be represented by these two distributions while 27% of the data from this region fail to be fitted by any of the candidate distributions.

It is interesting to note that the rainfall data for all rainfall durations from station 3519125 fail to be fitted by any of the candidate distribution functions and all three selected parameter estimation methods. As shown in Table 4.9, the extreme rainfall event recorded in year 2003 at this station is much higher compared to the mean rainfall value for respective durations. The presence of this extreme event causes failure in fitting the data with the candidate distributions. Furthermore, the standard deviation, skewness and kurtosis values of this station are much higher compared to other stations in the same region as shown in Table 4.9. Refer to APPENDIX 7 for comparison.

Table 4.8: Results of the frequency analysis for 6 rainfall stations across inland region with selected rainfall duration

State	Station Number	GEV	LN3	LP3	EV1	LN2	Fail
Kelantan	4819027	6	0	0	1	1	0
Pahang	3121143	7	0	0	1	0	0
	3519125	0	0	0	0	0	8
	3818054	4	1	0	2	1	0
	4023001	3	0	0	2	0	3
Johor	2330009	2	0	0	1	3	2

Table 4.9: Sample moments of station 3519125 with selected rainfall duration

Moments	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
Mean	32.4	48.3	63.7	89.2	98.5	101.0	110.6	147.7
Standard deviation	35.6	67.65	79.79	76.75	76.02	75.79	75.41	73.29
Skewness	4.411	5.78	5.92	5.66	5.49	5.47	5.182	4.449
Kurtosis	20.726	32.24	33.50	31.67	30.10	29.88	27.62	22.59
2003 AMS	225	450	541.5	542	542.5	543	543	546

Additionally, this study examined the fitness of the right tail of the distribution using Maximum Absolute Error instead of evaluating the overall fitness of the distribution by Goodness-of-fit (GOF) tests that have lower rejection power. Hence, more failures are detected in this study.

Table 4.10: Results of the frequency analysis across inland region for eight rainfall durations

Distribution	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
GEV	3	2	4	3	3	2	2	3
LP3	0	0	0	0	0	0	0	0
LN3	0	1	0	0	0	0	0	0
EV1	0	1	1	2	0	1	2	0
LN2	0	0	0	0	2	1	1	1
Fail	3	2	1	1	1	2	1	2
Total	6	6	6	6	6	6	6	6

As demonstrated in Table 4.10, the dispersion of the distribution functions corresponding to different rainfall durations are more noticeable in the inland region. As can be seen, the LN2 distribution only yields an adequate fit to longer duration (6-hour to 72-hour) rainfall, while GEV is able to give an adequate fit to both short and long duration rainfall.

Table 4.11 shows the results of the frequency analysis for 11 rainfall stations across the east coast region with the selected rainfall duration. It was found that the GEV, EV1 and LN2 distributions were able to provide adequate fits to the rainfall data in the east coast region, followed by the LN3 and LP3 distributions.

Table 4.11: Results of the frequency analysis for 11 rainfall stations across the east coast region for a total of six rainfall durations

State	Station Number	GEV	LN3	LP3	EV1	LN2	Fail
Kelantan	5718002	2	0	1	0	0	5
Terengganu	4734079	1	0	0	0	0	7
	4929001	0	1	0	2	2	3
	5331048	5	0	1	0	2	0
	5428001	3	1	1	1	2	0
	5428002	3	1	0	1	2	1
Pahang	3228174	0	0	0	0	0	8
	3231163	4	0	0	1	3	0
	3533102	0	2	1	1	3	1
Johor	1839196	4	2	0	1	1	0
	2235163	4	0	0	1	0	3

Stations 4734079 and 3228174 share the similar characteristics with station 3519125 from the inland region. Their sample moments are shown in APPENDIX 7. Almost all rainfall durations fail to be fitted by any combination of candidate distribution functions and parameter estimation methods. The standard deviation, skewness and kurtosis values for these stations are much higher compared to other stations in the same region due to the presence of outliers as shown in Table 4.12.

Table 4.12: Sample moments of station 4734079 and 3228174 with selected rainfall duration

Station	Moments	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
4734079	Mean	37.1	54.3	81.1	116.2	149.6	190.9	239.8	353.6
	Standard deviation	33.37	64.97	125.4	122.2	126.15	134.2	142.2	181.9
	Skewness	4.812	5.927	6.16	5.798	4.701	3.507	2.585	1.648
	Kurtosis	22.99	32.243	34.16	31.29	22.692	14.58	9.699	3.117
	2002 AMS	225	450	855	855	855	855.8	855.8	908.1
3228174	Mean	38.3	55.2	74.9	100.1	114.4	130.8	155.9	198.7
	Standard deviation	23.04	30.9	50.17	90.39	91.56	94.6	110.9	119.4
	Skewness	3.440	3.962	4.879	5.443	5.397	4.543	3.79	3.035
	Kurtosis	11.713	17.773	26.20	30.88	30.533	23.19	16.62	9.955
	1999 AMS	126.5	205	342.5	600.5	620	621.5	687.5	688.5

Apart from the number of rainfall data that fail to be fitted by any candidate distributions, EV1 and LN2 distributions also provide reasonable fit to the data as shown in Table 4.13.

Table 4.13: Results of the frequency analysis across the east coast region for eight rainfall durations

Distribution	15 min	30 min	1 hr	3 hrs	6 hrs	12 hrs	24 hrs	72 hrs
GEV	3	3	5	5	2	3	2	3
LP3	0	1	0	0	1	0	1	1
LN3	2	0	1	0	1	0	2	1
EV1	1	2	0	2	2	1	0	0
LN2	0	1	1	1	1	3	3	5
Fail	5	4	4	3	4	4	3	1
Total	11	11	11	11	11	11	11	11

Table 4.13 shows the comparison of the temporal variation for eight rainfall durations. The temporal variation in this region is more noticeable compared to other regions. The longer duration (six-hour to 72-hour) rainfall data have shown more substantial variations between the distributions chosen

compared to the shorter duration rainfall, as different candidate distributions are required to fit the rainfall data.

None of the candidate distribution functions can give an adequate fit to all stations across the study area. Also, none of the candidate distribution functions can give an adequate fit for all eight durations for any station. Hence, more than one distribution is needed to obtain better estimates of design rainfall for different regions in the study area.

Overall, the GEV distribution is able to fit rainfall data for most of the stations while LP3 is the least favourable distribution. For example, LP3 does not fit any rainfall data in the inland region while GEV is able to fit at least two out of six stations, as shown in Table 4.10. When the results are categorised according to each delineated region, the GEV distribution still outperformed other distribution functions in almost all the regions except for the east coast region. In addition, the longer duration rainfall shows more variability in the distribution of extreme rainfall, especially in the east coast region. Even though EV1 is the standard in Malaysia, its coefficient of skewness has a fixed value equal to 1.13 which limits its flexibility in fitting rainfall data (Smithers, 1998).

As can be seen from the analysis results, there are some data that could not be fitted by any of the candidate distribution functions, and the percentage of these data varies with the rainfall durations and regions. Overall, a higher percentage of shorter duration rainfall failed to be fitted by the candidate distributions. From Table 4.1 and Figure 4.2, more than 25% of the data from each 15-minute (22 out of 56 stations - 39%) and 30-minute (14 over 56 stations - 25%) rainfall fail to be fitted by all models since short duration rainfall largely results from convective rainfall. Besides, the ratio of stations that fail to be fitted by any candidate distribution is lower in the northwest region and higher in the central west and east coast regions due to geographical factors. For example, only 24% (4/17) of 15-minute data from the northwest region fail to be fitted by any candidate distribution, while 44% (8/18) and 45% (5/11) of the 15-minute rainfall from the central west and east coast regions fail to be fitted. As the Straits of Malacca becomes wider towards the north, the effects of land-sea breeze and local convection become more prevailing (Wong et al., 2009). Generally, there are two types of rainfall, that is, stratiform rainfall and convective rainfall where the convective rainfall lasts shorter and tends to be more intense (Lam et al., 2010).

Besides the presence of high skewness and kurtosis in the distribution of rainfall data, the non-stationary of data may cause the data failed to be fitted by any distribution function. The number of stations that could not be fitted by any candidate distributions are summarized in Figure 4.2. The rainfall data should come from the same distribution under the assumption that the data is stationary. However, given the changes in the magnitude and frequency of future extreme rainfall events, different statistical distributions and parameters can be expected mainly due to anthropogenic climate change (Hailegeorgis & Burn, 2009), as illustrated in Figure 2.1.

The subsequent section is aimed to detect non-stationary “trends” of the annual rainfall and annual maximum rainfall series. The non-stationarity of annual maximum rainfall might induce a significant effect on the estimation of the frequency distribution of extreme events (Brath at el., 1999).

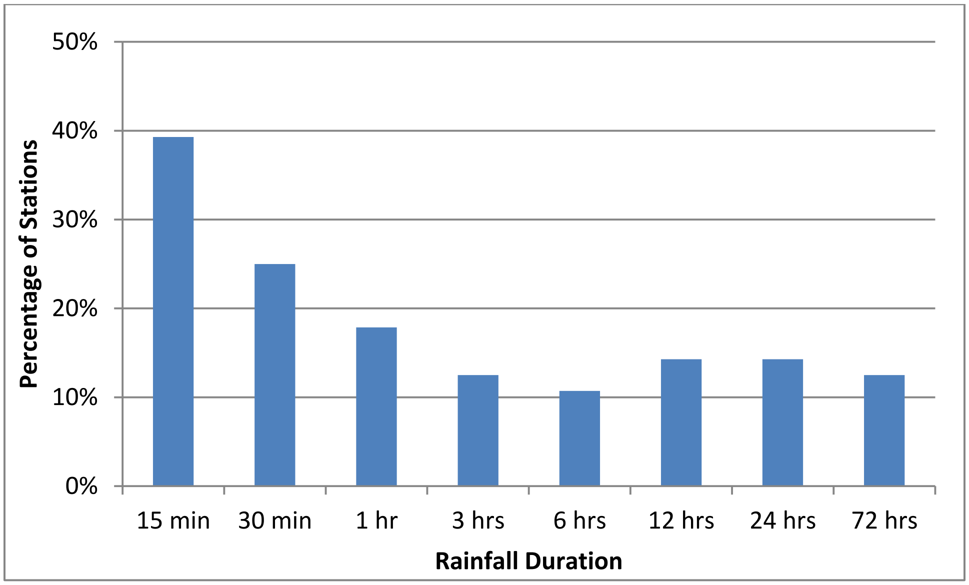

Figure 4.2: Rainfall data that fail to be fitted by any of the candidate distributions

4.2 MANN-KENDALL TREND TEST (MK TEST)

The results of the previous section suggest the presence of non-stationarity in rainfall data. The Mann-Kendall test is applied in evaluating the trend of annual rainfall, seasonal rainfall (northeast and southwest monsoon seasons), inter-monsoon rainfall (April and October) and annual maximum series for eight different rainfall durations, along with their respective spatial patterns.

The results and discussions are divided into five subsections which are 4.2.1 for the annual rainfall, 4.2.2 for seasonal rainfall (northeast and southwest monsoons), 4.2.3 for the inter-monsoon rainfall, 4.2.4 for annual maximum series and 4.2.5 for discussions. The correlation of spatial and temporal patterns are also considered.

4.2.1 Annual Rainfall

Overall, the recorded annual rainfall for most of the selected rainfall stations show an upward (increasing) trend as indicated by the MK test. The results of the MK test are classified for each region and the summary of the result is presented in Table 4.14.

Table 4.14: Significance of trend in annual rainfall for each region

Annual Rainfall	Positive Trend			Negative Trend			Total
	Not Significant	10% S.L.	5% S.L.	Not Significant	10% S.L.	5% S.L.	
North west	9	2	3	3	0	0	17
Central west	6	3	8	1	0	0	18
South west	0	0	1	1	1	1	4
Inland	4	0	1	1	0	0	6
East coast	5	2	2	2	0	0	11

Around 82% (46/56) of the stations experience an increase in annual rainfall volume, of which 43% (24/56) have shown statistically significant trends in terms of variations in annual rainfall, where 22 out of 56 are significantly positive and 2 out of 56 are significantly negative. On the other hand, only 10 out of 56 stations have indicated downward trends, of which only one station can be categorized to be “extremely likely” and “very likely” to exhibit a reduction in annual rainfall.

Even though less than half of the rainfall stations show significant trends, it is worthwhile to study the spatial distribution of the rainfall stations that exhibit a significant difference. The summary of the results is as shown in Figure 4.3.

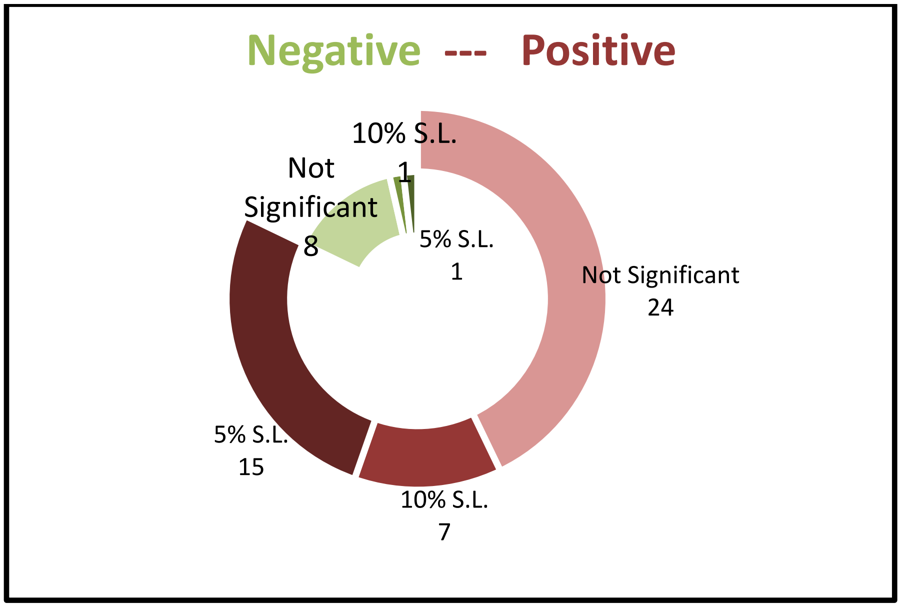

Figure 4.3: Significance of annual rainfall trend over Peninsular Malaysia

4.2.2 Seasonal Rainfall

To investigate the trend of seasonal rainfall across Peninsular Malaysia, the monthly rainfall data for each station has been segregated into four groups. The rainfall data from May to September will be used to represent the seasonal rainfall of the southwest monsoon while the data from November to March in the following year denotes the northeast monsoon rainfall. Accordingly, data from April and October are used to study the trend of inter-monsoon rainfall. The results of the trend test for monsoon rainfalls are as shown in Table 4.15.

Table 4.15: Overall results of MK test for seasonal rainfall

Seasonal Rainfall	Positive Trend			Negative Trend			Total
	Not Significant	10% S.L.	5% S.L.	Not Significant	10% S.L.	5% S.L.	
Northeast Monsoon	19	8	24	5	0	0	56
Southwest Monsoon	27	6	3	16	0	4	56

According to the results shown in Table 4.15, the northeast monsoon from November to March is bringing more rainfall to Peninsular Malaysia compared to the southwest monsoon season. The MK test reveals that more than 90% (51/56) of the stations have experienced rising trends. It is apparent that approximately 57% (32/56) of the stations show statistically significant upward trends in northeast monsoon rainfall. Overall, no significant downward trend was detected during this monsoon season.

On the other hand, the impact of the southwest monsoon is not as substantial as the northeast monsoon because considerably lesser data have shown a significant trend. In addition, the significant negative trend was not found during the northeast monsoon but was observed during the southwest monsoon. Only 23% (13/56) of the southwest monsoon rainfall shows significant trends, 16% (9/56) of which shows significant positive trends while 7% (4/56) are “extremely likely” to exhibit a reduction in seasonal rainfall.

Both the northeast and southwest monsoons have huge impacts on the characteristics of annual rainfall in Peninsular Malaysia as 10 months of each year are subjected to the influence of monsoon seasons. Also, it is necessary to study the spatial variation of monsoon rainfalls and how it influences the annual rainfall since spatial variation of water availability is crucial to development and management of water resources. The MK test results of both the seasonal rainfall for each region are summarized in Table 4.16.

Table 4.16: Significance of trend in northeast and southwest monsoon rainfall for each region

Monsoon Rainfall Trend		Positive Trend		Negative Trend		Not Significant
		10% S.L.	5% S.L.	10% S.L.	5% S.L.	
Northeast Monsoon	North west	3	8	0	0	6
	Central west	3	10	0	0	5
	South west	0	1	0	0	3
	Inland	0	1	0	0	5
	East	2	4	0	0	5
Southwest Monsoon	North west	1	0	0	2	14
	Central west	2	3	0	0	13
	South west	0	0	0	2	2
	Inland	0	0	0	0	6
	East	1	0	2	0	8

Based on the results shown in Table 4.16, 32 out of 56 stations have shown significant positive trends, and this signifies that the northeast monsoon brings more rainfall to the entire study area. The northwest (65% of stations) and central west (72% of stations) regions receive more rainfall compared to the other regions. Conversely, during the southwest monsoon, some of the regions have experienced a reduction in rainfall especially in the southwest region.

Significant decreasing trends have been detected during the southwest monsoon as six of the stations exhibit a reduction in rainfall during May to September across Peninsular Malaysia. For these cases, two of the stations in the southwest region have exhibited significant negative trends at a 5% significance level during the southwest monsoon and this is attributed to the reduction of annual rainfall. Significant negative trends are observed in two stations in the northwest region and two stations in the east coast area as well. However, it does not cause a significant impact on the annual rainfall since the annual rainfall is not experiencing a significant decreasing trend even though the seasonal rainfall is reduced during the southwest monsoon period.

4.2.3 Inter-monsoon Rainfall

To complete the study of rainfall trends in Peninsular Malaysia, the monthly rainfall data for the months of April and October have been used to represent the inter-monsoon rainfalls. The summary of the MK trend test results for both seasonal rainfalls in each region is shown in Table 4.17.

Table 4.17: Significance of trend in inter-monsoon rainfall for each region

Inter-Monsoon Rainfall Trend		Positive Trend		Negative Trend		Not Significant
		10% S.L.	5% S.L.	10% S.L.	5% S.L.	
April	North west	2	0	0	0	15
	Central west	1	2	0	0	15
	South west	0	1	0	1	2
	Inland	0	0	0	0	6
	East	1	0	0	0	10
October	North west	0	1	0	0	16
	Central west	2	2	0	0	14
	South west	0	0	0	1	3
	Inland	0	0	0	0	6
	East	0	0	0	0	11

Based on the results in Table 4.17, most of the rainfall stations (48 out of 56 stations in April and 50 out of 56 the stations in October) do not experience a significant trend during the inter-monsoon months. At the same time, inter-monsoon rainfall totals exhibits the least significant trend compared to both seasonal monsoon rainfalls. It is also seen from the results that rainfall during the inter-monsoon is not associated to the significant changes detected in the annual rainfall.

4.2.4 Annual Maximum Series

In the previous section, the annual and seasonal rainfalls are studied in relation to the change in rainfall volume and their spatial variation. The MK trend test indicates the volume of rainfall is increased in the northwest and central west region. However, the changes in heavy rainfall still remain unclear. Hence, in addition to the spatial variation, the variations in rainfall durations for the annual maximum series were subsequently studied.

4.2.4.1 Short duration rainfall

The summary of the MK test results of annual maximum series using 15-minute, 30-minute, one-hour and three-hour rainfall for each region are as shown in Table 4.18. The sub-hourly and hourly rainfalls in the northwest and central west region are most likely to experience increase in rainfall amount. More than 40% (7/17) of the sub-hourly rainfall and 1-hour rainfall has experienced a significant increasing trend for the northwest region while more than 60% (11/18) of the 30-minute rainfall in the central west region also experienced a significant upward trend.

Table 4.18: Significance of trend in annual maximum rainfall (short durations) for each region

Annual Rainfall Trend		Positive Trend			Negative Trend		
		Not Significant	10% S.L.	5% S.L.	Not Significant	10% S.L.	5% S.L.
North west	15-minute	5	6	1	5	0	0
	30-minute	6	3	5	3	0	0
	1-hour	8	3	4	2	0	0
	3-hour	12	1	0	4	0	0
Central west	15-minute	11	2	3	2	0	0
	30-minute	6	1	10	1	0	0
	1-hour	10	1	7	0	0	0
	3-hour	10	0	4	4	0	0
South west	15-minute	2	0	0	2	0	0
	30-minute	1	1	0	2	0	0
	1-hour	1	0	1	2	0	0
	3-hour	2	0	0	2	0	0
Inland	15-minute	3	2	1	0	0	0
	30-minute	3	2	1	0	0	0
	1-hour	5	0	0	1	0	0
	3-hour	4	0	0	2	0	0
East coast	15-minute	9	0	2	0	0	0
	30-minute	5	2	3	1	0	0
	1-hour	8	2	1	0	0	0
	3-hour	4	2	2	3	0	0

4.2.4.2 Long duration rainfall

The MK trend test was carried out on the annual maximum series using six-hour, 12-hour, 24-hour and 72-hour rainfall and the results have been summarized according to the delineated regions as shown in Table 4.19. Nearly 30% (5/18) of the 72-hour rainfall in the central west region has experienced a significant increasing trend while long duration rainfalls in the rest of the regions were found to be stationary.

Table 4.19: Significance of trend in annual maximum rainfall (long durations) for each region

Annual Rainfall Trend		Positive Trend			Negative Trend		
		Not Significant	10% S.L.	5% S.L.	Not Significant	10% S.L.	5% S.L.
North west	6-hour	10	1	0	6	0	0
	12-hour	7	1	0	9	0	0
	24-hour	11	0	1	5	0	0
	72-hour	7	1	2	7	0	0
Central west	6-hour	9	2	3	4	0	0
	12-hour	11	1	3	3	0	0
	24-hour	10	1	3	3	1	0
	72-hour	7	2	3	6	0	0
South west	6-hour	2	0	0	2	0	0
	12-hour	2	0	0	2	0	0
	24-hour	1	0	0	3	0	0
	72-hour	0	0	1	3	0	0
Inland	6-hour	5	0	0	1	0	0
	12-hour	5	0	0	1	0	0
	24-hour	5	0	0	1	0	0
	72-hour	2	0	0	3	1	0
East coast	6-hour	6	1	2	2	0	0
	12-hour	6	0	2	3	0	0
	24-hour	8	0	0	3	0	0
	72-hour	7	0	0	3	1	0

From the test results of the annual maximum series, short duration rainfall indeed have shown more significant growth compared to rainfall with longer durations.

4.2.5 Discussion

According to the results of the MK trend test on annual rainfall, 24 out of 56 stations show significant changes in trend with 39.3% (22/56) showing an upward trend and 3.6% (2/56) showing a downward trend. The MK test analysis shows the greatest significant upward trend in the central west region for the period 1970-2011. The central west region covers the southern part of Perak, the entire region of Selangor, Kuala Lumpur, Negeri Sembilan and Melaka. These locations are more likely to have increasing trends in annual rainfall compared to other regions, with more than 60% (11/18) of the rainfall stations categorised as "extremely likely" and "very likely" to have more rainfall.

In addition, the most intense increment of rainfall occurred during the northeast monsoon season in the central west region. Around 94% (17/18) of the stations in the central west region receive more rainfall from November to March in the following year and 72% of the stations (13 out of 18 stations) have experienced significant upward trends, refer APPENDIX 9. This indicates that the significant increasing trends of the northeast monsoon rainfall are correlated with the upward trends in annual rainfall for this region compared to the northwest region. The delineated central west region is more sensitive towards these changes, as it consists of highly urbanised areas such as Kuala Lumpur and state of Selangor. According to Jaafar (2004), in year 2000, Kuala Lumpur was the most urbanised area with a coverage of 100%, followed by the state of the Selangor with 88% of the land categorised as an urban area.

The significant increasing trend observed in the central west region is reflected in the findings of Amirabadizadeh et al. (2014). Amirabadizadeh et al. (2014) investigated signs of climate change at one of the most urbanised river basins (Langat River Basin) in the middle section of the central west region. The results generally indicate that there is a climate change signal that emerged in the year 2000 for annual rainfall and for maximum and minimum temperatures as determined from Mann-Kendall rank statistics tests with study periods ranging between 27 and 41 years.

At the same time, the northwestern region of Peninsular Malaysia also received more rainfall during northeast monsoon compared to the southwest monsoon as 65% (11/17) of the stations exhibit significant positive trends. These two regions located at the west coast of Peninsular Malaysia experience more rainfall during the northeast monsoon due to the cold surge traveling from Siberia and less rainfall during the southwest monsoon because of the rain shadow effect from the Sumatran mountain range (Desa et al., 2001).

These significant changes found in the northwest and central west regions show a close relation between the impact of climate change and the occurrence of heavy rainfall. Trenberth (2010) and Rougé et al. (2013) also pointed out that increased heating leads to inceased water vapour in the atmosphere and hence, induced occurrence of more intense rainfall.

From the trend test results, the least significant trend is detected in the inland region which consists of six rainfall stations that are located approximately

110 km away from the nearest coastline (not obstructed by high ground). The significant increasing trend is only observed in 15-minute and 30-minute rainfall for this region. One of the possible reasons could be related to the increased temperature due to climate change or urban heat island effect, which leads to an increase of atmospheric moisture acquisition over the ocean (Pan et al., 2011). This explains why the significant increasing trends are observed over those stations in the east and west coasts except for the inland region. In addition, the inland region is less vulnerable to changes due to the topographic blocking effects (Pan et al., 2011).

For annual maximum series data, 13.8% of the stations in the Northwest region (out of 29 stations that show significant trend, 4 of them failed to be fitted by any of the candidate distributions), 21% (10/47) of the stations in the Central West region, 0% of the Southwest region, 43% (3/7) of the Inland region, and 30% (6/20) of the stations in the east coast region show a significant trend and fail to be fitted by any candidate distribution function.

Overall, different degrees of change of trends have been detected in annual rainfall, seasonal rainfalls and annual maximum rainfall series. Even though less than half of the results of the MK trend test on annual rainfall show significant changes in trend, more than half (32/56) of the stations in Peninsular Malaysia show statistical significance in upward trends in northeast monsoon rainfall, especially in the northwest (65% of stations) and central west region (72% of stations). The results imply climate change for rainfall in Peninsular Malaysia especially during the northeast monsoon.

4.3 CHANGE-POINT ANALYSIS

4.3.1 Non-stationary Tests

From the results of the MK test, it is shown that the central west region has experienced the most intense increment in annual rainfall, seasonal rainfall and annual maximum rainfall series. Furthermore, short duration rainfall also exhibits a significant increasing trend compared to long duration rainfall.

As the presence of a trend in the rainfall series indicates the possible presence of non-stationarity in the data, hence, this section aims to evaluate the stationarity of the rainfall series. Both Mood's median test and the Mann-Whitney (MW) test were applied to evaluate the statistical significance of changes in annual rainfall and annual maximum rainfall for two different sub-series (all the available data before year 1994 and from 1995 to 2011). In the following sections, the sub-series prior to year 1995 will be known as the first sub-series and, the sub-series posterior to year 1995 will be referred to as the second sub-series.

For Mood's median test, the critical chi-square value with one degree of freedom at the 0.90 probability level is 2.71. For the Mann-Whitney test, the test statistic is approximated to the normal distribution, and the critical value corresponding to the 0.90 significance level is 1.645. The bold numbers in the following tables denote significant differences between the two sub-series prior and posterior to year 1995. The results and discussion for annual rainfall, short and long duration annual maximum rainfall are described further in section 4.3.1.1 to 4.3.1.4 using both non-stationary tests.

4.3.1.1 Annual rainfall

The difference degrees of non-stationarity were identified in the annual rainfall series for each delineated region using both the non-stationary tests. The results are as presented in Table 4.20.

Table 4.20: Non-stationary test results for annual rainfall

Region	State	Stations	Annual Rainfall	
			Median	MW
Northwest	Perlis	6401002	2.245	1.493
	Kedah	5704055	1.129	0.925
		5806066	**2.948**	0.979
		5808001	**3.394**	1.025
		6108001	1.303	**1.890**
		6206035	1.172	**1.694**
	Pinang	5302001	0.034	0.370
		5302003	1.003	0.190
		5402001	0.111	0.428
		5402002	1.003	0.966
	Perak	4209093	0.111	0.903
		4311001	**6.060**	**2.895**
		4409091	1.172	1.601
		4511111	1.303	0.640
		4708084	**9.745**	**2.834**
		4811075	0.279	1.081
		5210069	**2.948**	**2.580**
Central west	Perak	4010001	1.172	1.032
	Selangor	2917001	1.003	**1.695**
		3117070	2.406	1.601
		3118102	0.000	0.324
		3411017	0.201	1.032
		3416002	2.000	**2.197**
		3516022	1.172	1.111

Region	State	Stations	Annual Rainfall	
			Median	MW
Central west	Selangor	3613004	1.667	1.098
		3710006	0.201	0.106
	Kuala Lumpur	3116003	**5.461**	**2.804**
		3116006	**9.529**	**3.840**
		3216001	0.033	0.170
		3217001	0.033	0.099
		3217002	**13.646**	**3.370**
		3217003	**6.060**	**2.590**
	Negeri Sembilan & Melaka	2719001	**12.379**	**3.731**
		2722002	1.172	**2.038**
		2224038	**2.948**	**2.038**
Southwest	Johor	1437116	**2.948**	**1.958**
		1534002	0.029	0.684
		1737001	2.2452	**1.737**
		2025001	2.2452	1.585
Inland	Kelantan	4819027	0.102	0.178
	Pahang	3121143	1.003	0.808
		3519125	**3.083**	**2.464**
		3818054	1.500	0.973
		4023001	0.106	0.367
	Johor	2330009	0.201	1.111
East coast	Terengganu	4734079	2.558	1.059
		4929001	0.111	0.871
		5331048	0.033	0.793
		5428001	1.059	1.378
		5428002	1.059	0.947
	Pahang	3228174	0.118	0.809
		3231163	2.661	1.277
East coast	Pahang	3533102	0.232	0.975
	Johor	1839196	0.201	0.847
		2235163	0.125	0.850
	Kelantan	5718002	0.313	0.437

4.3.1.2 Annual maximum short duration rainfall

Mood's median test and the Mann-Whitney test indicated that there is a statistically significant difference between the two sub-series especially for short duration rainfalls. However, different regions show a different degree of non-stationarity in the data. The results of both tests using 15-minute, 30-minute, one-hour and three-hour annual maximum rainfall for each region are as presented in Table 4.21.

Table 4.21: Non-stationary test result for annual maximum rainfall (short duration)

Region	State	Stations	15-minute		30-minute		1-hour		3-hour	
			Median	MW	Median	MW	Median	MW	Median	MW
North-west	Perlis	6401002	0.70	1.63	2.25	**1.91**	2.25	**2.04**	2.25	**1.80**
	Kedah	5704055	**8.19**	**3.06**	**3.14**	**2.25**	**6.15**	**1.87**	1.13	1.53
		5806066	1.17	0.61	0.12	0.20	0.20	0.07	0.20	0.49
		5808001	0.14	0.40	0.14	0.11	**3.39**	0.90	0.14	0.48
		6108001	0.11	1.13	0.81	0.59	0.03	0.09	0.03	0.46
		6206035	0.20	1.02	**2.95**	**1.71**	1.82	1.30	1.17	0.82
	Pinang	5302001	**2.95**	**2.30**	**2.95**	**2.16**	**2.95**	1.47	0.20	0.57
		5302003	0.11	0.38	1.00	0.49	1.00	0.59	1.00	1.17
		5402001	1.00	0.41	1.00	0.46	1.00	0.02	1.00	0.97
		5402002	**9.03**	**2.93**	**5.46**	**2.96**	**5.46**	**2.36**	1.00	0.56
	Perak	4209093	0.00	0.25	**2.79**	0.81	0.11	0.84	0.11	0.70
		4311001	**3.25**	**2.55**	**6.06**	**3.00**	**6.06**	**3.02**	**9.75**	**2.71**
		4409091	**2.95**	1.55	1.17	**2.36**	1.17	1.63	1.82	1.31
		4511111	0.03	0.35	**3.25**	**2.01**	**6.06**	**2.47**	1.30	1.45
		4708084	0.03	0.18	0.03	0.43	0.23	0.15	0.23	0.78
	Perak	4811075	0.28	0.90	1.50	0.87	1.50	0.79	**3.69**	1.17
		5210069	1.17	**1.75**	**2.95**	**2.30**	1.17	**1.73**	1.82	1.23
Central west	Perak	4010001	1.17	**1.77**	0.20	1.19	0.20	0.32	1.17	1.23
	Selangor	2917001	1.00	0.68	**2.79**	**2.14**	**2.79**	**2.35**	**9.03**	**3.09**
		3117070	1.67	**1.93**	1.17	**1.92**	2.41	**2.10**	2.41	1.43

Region	State	Stations	15-minute		30-minute		1-hour		3-hour	
			Median	MW	Median	MW	Median	MW	Median	MW
Central west	Selangor	3118102	0.00	0.32	1.50	0.68	0.50	0.87	0.50	0.18
		3411017	**2.95**	**2.17**	0.42	1.15	0.42	0.56	0.03	0.29
		3416002	0.00	0.50	1.50	0.94	1.50	0.72	0.28	0.05
		3516022	**17.11**	**3.33**	**8.91**	**2.94**	1.17	**1.68**	0.15	0.45
		3613004	**5.53**	**2.28**	**5.53**	1.54	1.17	1.05	1.17	1.05
		3710006	1.67	1.47	1.67	**1.76**	1.17	0.33	0.42	0.34
	Kuala Lumpur	3116003	**5.46**	**2.27**	**5.46**	**2.17**	0.11	0.98	1.00	1.00
		3116006	1.89	**1.72**	**9.66**	**3.77**	**26.47**	**4.67**	**9.53**	**3.60**
		3216001	1.23	1.30	**3.08**	**2.56**	1.23	1.57	1.23	1.22
		3217001	0.22	0.74	1.23	**1.91**	**13.65**	**3.75**	1.23	**1.67**
		3217002	**11.15**	**2.82**	**13.65**	**4.19**	**9.29**	**3.51**	0.01	1.53
		3217003	**6.06**	**2.30**	**14.30**	**3.66**	**6.06**	**2.35**	1.30	1.43
	Negeri Sembilan & Melaka	2719001	**5.01**	**2.16**	**5.53**	**3.33**	**17.29**	**3.71**	**5.01**	**2.92**
		2722002	**6.32**	**3.00**	**5.01**	**2.99**	**4.50**	**3.03**	**5.53**	**3.22**
		2224038	0.67	0.25	0.67	0.21	0.20	1.03	0.67	0.05
South-west	Johor	1437116	0.03	0.16	0.20	0.33	0.20	0.53	0.20	1.11
		1534002	1.50	1.33	**6.86**	**1.84**	**6.86**	**2.13**	1.50	0.94
		1737001	0.23	1.33	0.29	0.43	0.70	0.91	0.70	0.12
		2025001	0.03	0.08	0.03	0.66	0.70	0.52	0.03	0.03
Inland	Kelantan	4819027	1.17	0.77	1.17	1.10	0.03	0.13	0.01	0.09
	Pahang	3121143	**7.06**	**2.69**	**2.79**	**2.68**	**2.79**	**2.06**	1.00	1.43
		3519125	**12.88**	**3.00**	**5.77**	**2.44**	1.23	1.01	1.95	**1.69**
		3818054	**3.69**	1.44	1.50	1.12	0.03	0.41	2.44	1.21
		4023001	2.66	0.78	0.96	0.73	0.11	0.07	0.47	0.82
	Johor	2330009	1.17	1.01	0.20	1.16	0.03	0.32	0.03	0.58
East Coast	Terengganu	4734079	0.92	0.82	0.03	0.33	0.20	0.29	1.17	0.17
		4929001	**2.79**	**1.90**	1.00	1.62	0.11	0.97	0.11	1.32
		5331048	1.23	0.77	0.22	0.82	1.23	0.54	0.22	0.11
		5428001	0.12	0.71	1.06	**2.00**	**2.94**	**2.05**	1.89	1.26
		5428002	1.06	1.29	0.12	1.12	0.12	0.81	**5.77**	**1.98**
	Pahang	3228174	**2.94**	**2.74**	**2.94**	**2.03**	1.06	1.33	0.12	0.05
		3231163	0.96	1.38	0.38	1.22	0.96	1.28	**5.22**	**2.16**
		3533102	**14.30**	**3.37**	**6.06**	**1.98**	**6.06**	**2.01**	1.30	1.25
	Johor	1839196	0.20	0.89	**8.91**	**2.69**	1.17	1.20	0.03	0.07
		2235163	0.13	0.55	**3.14**	**1.79**	0.13	0.59	0.54	0.38
	Kelantan	5718002	**6.15**	**2.51**	**6.15**	**3.19**	**10.17**	**3.19**	1.13	**1.74**

4.3.1.3 Annual maximum long duration rainfall

Both tests imply stationarity in most of the long duration rainfall series compared to short duration rainfall. The median test and Mann-Whitney test results based on annual maximum series using six-hour, 12-hour, 24-hour and 72-hour rainfall for each region are as presented in Table 4.22.

Table 4.22: Non-stationary test result for annual maximum rainfall (long duration)

Region	State	Stations	6-hour		12-hour		24-hour		72-hour	
			Median	MW	Median	MW	Median	MW	Median	MW
North-west	Perlis	6401002	2.25	1.17	0.23	0.49	0.23	0.02	0.03	0.43
	Kedah	5704055	1.13	0.36	1.13	0.47	0.13	0.21	1.13	0.64
		5806066	0.92	0.13	2.11	0.74	2.11	0.56	0.20	0.05
		5808001	0.00	0.21	0.00	0.63	0.14	0.92	0.14	0.90
		6108001	0.23	0.38	0.03	0.46	**6.06**	1.52	**6.06**	**2.23**
		6206035	1.17	1.27	1.17	1.09	0.20	1.22	**2.95**	**1.96**
	Pinang	5302001	0.20	0.49	0.20	0.77	1.17	0.50	0.03	0.11
		5302003	0.11	1.38	0.11	0.90	0.11	1.16	1.00	1.22
		5402001	**2.79**	1.13	1.00	1.19	0.11	0.27	1.00	0.08
		5402002	0.00	0.65	0.11	0.52	0.11	0.70	0.11	0.49
	Perak	4209093	0.11	0.03	0.11	0.08	0.11	0.40	1.00	0.06
		4311001	**9.75**	**2.97**	**14.30**	**3.11**	**9.75**	**3.47**	**3.25**	**2.83**
		4409091	1.82	1.14	1.17	1.20	0.67	0.04	0.03	1.16
		4511111	1.30	1.07	1.30	1.07	0.19	0.44	1.30	0.70
		4708084	1.30	0.61	1.30	0.50	1.30	0.53	0.03	0.66
		4811075	**3.69**	0.90	0.28	0.41	0.03	0.07	1.50	0.11
		5210069	1.17	1.46	**2.95**	1.58	**2.95**	1.48	**8.91**	**2.30**
Central west	Perak	4010001	1.17	0.97	1.17	0.97	0.03	0.19	0.20	0.33
	Selangor	2917001	**2.79**	**2.61**	**2.79**	**2.01**	**5.46**	**2.19**	**2.79**	**1.76**
		3117070	0.42	**1.68**	1.17	1.40	0.42	1.13	1.17	1.02
		3118102	0.00	0.13	0.28	0.07	0.50	0.14	2.44	**1.82**
		3411017	1.07	0.45	1.67	0.69	0.03	0.30	2.11	1.15
		3416002	0.03	0.23	0.28	0.61	0.03	0.50	1.50	**2.09**
		3516022	0.20	1.02	0.00	0.58	0.20	0.78	**2.95**	1.30
		3613004	**5.53**	**1.83**	**3.75**	**1.79**	1.67	1.32	0.20	0.85
		3710006	0.03	0.15	0.00	0.15	**3.75**	1.52	**1.43**	0.95

Region	State	Stations	15-minute		30-minute		1-hour		3-hour	
			Median	MW	Median	MW	Median	MW	Median	MW
Central west	Kuala Lumpur	3116003	**2.79**	0.97	0.09	0.94	**2.79**	**1.97**	**9.03**	**2.61**
		3116006	**9.53**	3.67	**9.53**	3.50	**9.53**	**3.07**	**5.77**	**3.46**
		3216001	1.23	0.64	0.69	0.61	0.69	1.29	0.69	0.98
		3217001	0.56	0.81	0.22	0.60	1.23	0.88	0.22	0.61
		3217002	0.22	1.44	1.23	**1.67**	1.23	1.13	**3.08**	1.63
		3217003	0.23	1.22	0.23	0.61	0.03	0.20	0.70	0.00
	Negeri Sembilan & Melaka	2719001	1.52	**2.50**	0.92	**1.79**	0.20	0.68	**2.95**	**1.85**
		2722002	**5.53**	**3.24**	**5.01**	**2.75**	0.69	**2.06**	1.17	1.35
		2224038	0.03	0.08	1.17	0.90	**2.95**	1.42	0.20	0.99
South-west	Johor	1437116	**2.95**	**1.89**	**3.94**	**1.76**	0.03	0.93	**5.53**	**2.54**
		1534002	0.28	0.54	0.03	0.11	0.28	0.00	0.03	0.07
		1737001	0.70	0.06	0.03	0.24	0.70	0.21	0.70	1.43
		2025001	0.23	0.23	0.03	0.35	0.23	0.05	1.30	0.00
Inland	Kelantan	4819027	0.20	0.53	0.20	0.21	0.20	0.28	0.01	0.66
	Pahang	3121143	0.11	1.14	1.00	1.16	0.11	0.44	1.00	0.70
		3519125	0.01	1.32	0.22	1.32	**5.77**	**1.83**	1.23	1.42
		3818054	0.03	0.23	**3.69**	0.67	0.28	0.41	0.03	0.23
		4023001	0.96	1.00	0.96	1.38	0.11	1.22	2.66	**2.22**
	Johor	2330009	0.20	1.11	0.20	1.19	0.20	1.03	0.03	0.56
East coast	Terengganu	4734079	0.20	0.42	0.03	0.77	1.17	0.95	0.03	0.15
		4929001	1.00	1.54	**2.79**	**1.98**	1.00	1.16	**2.79**	1.09
		5331048	0.03	0.13	0.03	0.77	0.69	0.82	0.03	0.65
		5428001	0.12	0.81	0.12	0.12	0.12	0.36	0.12	0.71
		5428002	1.06	1.46	1.06	1.36	1.06	0.50	0.12	0.26
	Pahang	3228174	1.06	0.90	0.12	1.02	0.12	0.12	1.06	0.31
		3231163	2.66	**2.31**	0.96	1.25	0.11	0.10	0.11	0.26
		3533102	0.23	0.64	0.23	0.03	0.23	0.31	0.23	0.64
	Johor	1839196	0.67	0.12	0.67	0.24	0.20	0.60	0.20	0.45
		2235163	0.13	0.36	0.13	1.02	1.13	0.59	1.13	1.51
	Kelantan	5718002	0.13	0.93	0.13	0.89	1.13	0.17	0.13	0.02

4.3.1.4 Discussion

Significant differences were detected at the 10% significance level for the annual rainfall sub-series prior and posterior to year 1995 (except for the east coast region). Similar results were also found at the same significance level for both sub-series based on short and long duration annual maximum rainfall for all regions. The summary is as shown in Table 4.23 and are based on either one of the non-stationary tests. In this case, the Mann-Whitney test shows greater power in detecting the non-stationarity except for long duration annual maximum rainfall series in the northwest region.

Table 4.23: Summary of non-stationary tests results

Region	Annual Rainfall	15-minute	30-minute	1-hour	3-hour	6-hour	12-hour	24-hour	72-hour
North-west	7/17	6/17	10/17	8/17	3/17	3/17	2/17	3/17	4/17
Central west	9/18	11/18	13/18	9/18	5/18	7/18	6/18	6/18	9/18
South-west	2/4	0/4	1/4	1/4	0/4	1/4	1/4	0/4	1/4
Inland	1/6	3/6	2/6	1/6	1/6	0/6	1/6	1/6	1/6
East coast	0/11	4/11	6/11	3/11	3/11	1/11	1/11	0/11	1/11

Non-stationarity was detected in annual rainfall data for most of the regions except for east coast region. The test results show that non-stationarity in the data is substantial, ranging from 41% (7/17 in the northwest) to 50% (2/4 in the southwest) over the west coast regions. Only one out of six stations from the inland region has shown signs of non-stationarity in the annual rainfall while the east coast region has not shown any such traits.

For the annual maximum series, the test results show stronger evidence of non-stationarity in short duration annual maximum rainfall especially for the northwest and the central west regions. Non-stationarity was detected in nearly 35% of 15-minute rainfall series and more than 47% of the 30-minute and one-hour annual maximum rainfall series in northwest region. For the central west region, 61% of the 15-minute rainfall series and more than 50% of the 30-minute and one-hour annual maximum rainfall series in the central west region have shown non-stationarity. While for the inland and east coast regions, the non-stationarity is only noticeable in 15-minute and 30-minute rainfall series.

On the other hand, the long duration annual maximum series are stationary for most of the regions except for the central west region as stated in Table 4.22. Non-stationarity was detected in 72-hour rainfall series for the central west region whereby more than one-third of the stations have shown significant non-stationarity in the observed records. Almost all of the long duration rainfall have shown a weaker sign of non-stationarity compared to short duration rainfall except for southwest region. The results of the MK test along with the non-stationary tests for annual rainfall and annual maximum series as well as the data that could not be fitted by candidate distribution functions are as listed in APPENDIX 4.

Based on the change-point (year 1995), the influence of non-stationarity is more noticeable in short duration rainfall. This could be due to the high spatial and temporal variability in the data (Verdon-Kidd & Kiem, 2015). It is also possible that the analysis on short duration rainfall is subject to greater sampling errors compared to long duration rainfall (Whitehouse, 1985). It is important to note that non-stationarity in short duration rainfall or sub-daily rainfall have been reported in other regions as well, for example different regions in Australia (Westra & Sisson, 2011; Yilmaz et al., 2014) and Sicily (Bonaccorso et al., 2005). Since extreme rainfall trends can show large variations over short durations (Bonaccorso et al. 2005), it is therefore essential to conduct extreme rainfall trend analysis at finer temporal scales (with short duration rainfall). This is more so since urban flash flooding is the product of heavy rainfalls over short durations.

4.3.2 Sequential Mann-Kendall Test (SMK Test)

The results of the previous section imply that the change-point applied in non-stationary tests will be used as the starting point for a new trend in the time series. Hence, this section aims to verify the change-point (year 1995) by comparing it with the starting point of significant trend identified using the SMK test.

Figure 4.4 shows the trends variation and change-point test for annual rainfall for one of the station 5718002 in Kelantan. The horizontal dashed lines in Figure 4.4 represent the critical values for the 0.1 and 0.05 significance levels, respectively. When the progressive series and backward series cross each other and diverge above either threshold value, we can infer that a statistically significant trend has developed from that intersection point.

As shown in Figure 4.4, the rainfall series may have more than one change-point above the specific significance levels. The annual rainfall series at station 5718002 in Kelantan has three change-points, which falls between years 1990 to 1991, year 1998 and between years 2008 to 2009.

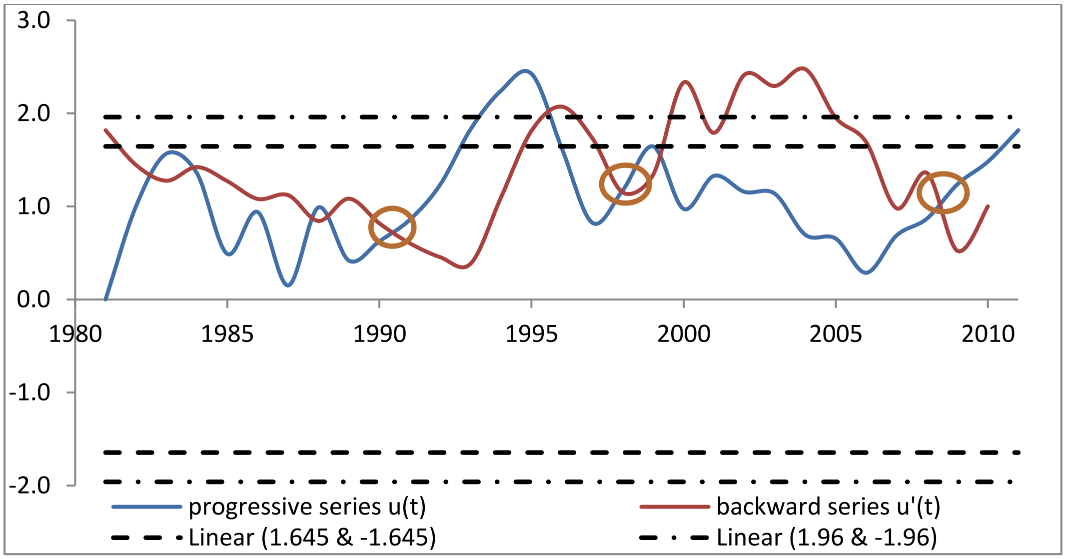

Figure 4.4: SMK plot for annual rainfall at station 5718002

The results of the SMK test are organized according to the delineated region. Table 4.24 shows the summary of the change-points detected above the specific threshold values and are denoted by plus or minus signs to indicate whether a significant increasing or decreasing trend was detected for each delineated region.

Table 4.24: Summary of change-points detected for each delineated region

Regions	State	Station Number	Significant Change-points
Northwest	Perlis	6401002	1976 (-) 1978-79 (+)
	Kedah	5704055	1982 (+)
		5806066	
		5808001	1983-84 (+)
		6108001	1982 (+)
		6206035	
	Penang	5302001	1971 (-)
		5302003	1983 (+)
		5402001	
		5402002	
	Perak	4209093	
		4311001	1990-91 (+)

Regions	State	Station Number	Significant Change-points
Northwest	Perak	4409091	1983 (+) 1986-87 (+) 2009 (+)
		4511111	1979-80 (+)
		4708084	1994 (+)
		4811075	1979 (+)
		5210069	1992 (+)
Central west	Perak	4010001	1979-80 (+)
	Selangor	2917001	1977 (+) 1992 (+)
		3117070	1981 (+) 2000 (+)
		3118102	
		3411017	
		3416002	2005 (+)
		3516022	
		3613004	1989 (+) 2007(+)
		3710006	1990 (+)
	Kuala Lumpur	3116003	1991 (+)
		3116006	1994 (+)
		3216001	
		3217001	1973 (-)
		3217002	1996 (+)
		3217003	1996-97 (+)
	Negeri Sembilan	2719001	1993 (+)
		2722002	1979 (+)
	Melaka	2224038	1987 (+)
Southwest	Johor	1437116	1977-78 (+) 1979-80 (+) 1981-82 (+) 1991-92 (+) 1998 (+)
		1534002	1987 (-)
		1737001	1992 (-)
		2025001	1980 (-) 1985-86 (+)
Inland	Kelantan	4819027	1979 (+)
	Pahang	3121143	1982 (-)
		3519125	1994 (+)
		3818054	
		4023001	
	Johor	2330009	1982 (+)
East coast	Kelantan	5718002	1990-91 (+) 1998 (+) 2008-09 (+)
	Terengganu	4734079	1972-73 (+)
		4929001	
		5331048	
		5428001	1982-83 (+) 2006-07 (+)

Regions	State	Station Number	Significant Change-points
East coast	Terengganu	5428002	1984 (+) 1990-91 (+) 2006-07 (+)
	Pahang	3228174	
		3231163	1982-83 (+) 1992 (+)
		3533102	1977 (+)
	Johor	1839196	1976 (+)
		2235163	

None of the regions have shown a clear indication of the starting point of a significant trend. In particular, the results suggest that most of the change-points are scattered along the time series. For the northwest region, most of the change-points fall between the years of 1978 to 1984 while the majority of change-points were found in the range of 1989 to 1997 for the central west region. On the other hand, the change-points detected for other regions were found to be distributed along the time frame without a distinct pattern.

The change-points in the data series may correspond to underlying change-points of local climate if all the rainfall series exhibit change within a common range of years but that could not be found in this case.

As mentioned earlier, the SMK test was an attempt to verify the selected change-point (year 1995). However, the analysis reveals inconsistent results since the detected change-points vary across the rainfall series for all the stations as shown in Table 4.24. Without consistency for the range of change-points, those change-points are not practicable and hence, the SMK test was not applied on the annual maximum series. It is possible that the analysis is sensitive to a change in instrumental arrangements and measuring conditions (Bisai et al., 2014) or climatic oscillation at the inter-annual time scale such as El Niño and La Niña

(Verdon-Kidd & Kiem, 2015). Such phenomena are characterized by oscillation between warm and cold events. As it turns out, some of the detected change points coincide with a number of reported El Niño and La Niña events. For instance, one of the stronger El Niño events (1982-1983) was a common change point detected throughout the study area (be seen eight times throughout the study area). This suggests that the identified change-points may be due to large scale oscillation rather than long term climate variability.

Accordingly, the potential change points were determined and the annual maximum rainfall series was converted into two sub-series. In this case, year 1995 is applied as the change-point and the following section will validate the changes in distribution of annual maximum rainfall records prior and posterior to 1995.

4.4 FREQUENCY ANALYSIS USING TWO SUB-SERIES DATA

4.4.1 Changes in Probability Distribution

Changes in trend and the presence of non-stationarity have been detected in the observed rainfall series across the study area. Changes over time in historical periods can be assessed using statistical trend analysis, which allows for the investigation of whether recent historical changes in the frequency and amplitude of rainfall extremes can be detected. This section explores whether partitioning the data series prior to analysis can improve the fit of the distribution function and provide insight into rainfall distribution patterns. The annual maximum rainfall series are divided into two sub-series (first and second sub-series) with year 1995 as the change-point; these have been evaluated based on the assessment procedures.

The assessment of the changes in rainfall distributions were carried out by comparing the distributions between the second sub-series and full series data; and, the distributions between the first and second sub-series data. Overall, the results of the assessment can be grouped into four categories as follows:

i. Significant difference has been detected between full series and second sub-series or between the two sub-series data; changes of distributions have been detected.
ii. Same distribution function and parameter estimation method are adopted to represent all three data series. Hence, no change has been detected.
iii. Same distribution function is used to represent the all three data series but with fitted by different parameter estimation methods.
iv. All candidate distributions are inadequate to fit the second sub-series data; fail to be fitted by any candidate distributions.

APPENDIX 5 shows the hydrologic frequency analysis results for all duration rainfall series. The results are summarized and further classified into short duration rainfall and long duration rainfall in the following sections. Figure 4.5 (all 4 short duration) and 4.6 (all 4 long duration) summarize the hydrologic frequency analysis results for all duration rainfall series. The details are available in APPENDIX 5.

4.4.1.1 Short Duration Rainfall

The tendency of short duration rainfalls towards having different distributions in representing the rainfall series is fairly substantial, as more than 50% of the rainfall stations experienced changes in distributions except for the east coast region. Figure 4.5 shows the results of the assessment for each delineated region.

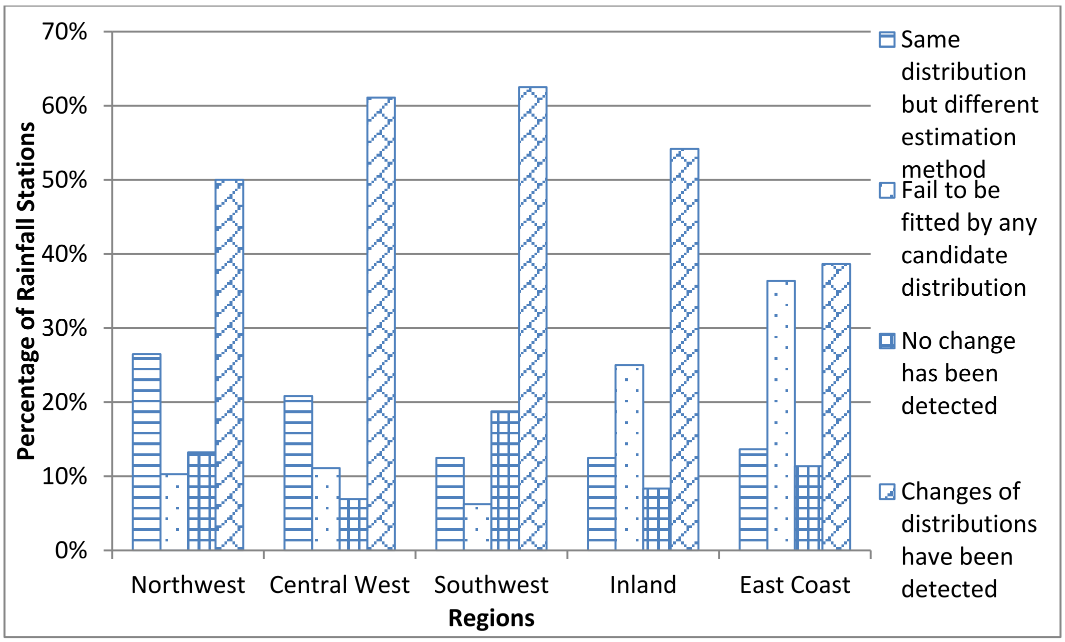

Figure 4.5: Assessment of the changes in rainfall distributions for the five regions (short duration rainfall)

The candidate distribution functions are inadequate to fit a large number of short duration rainfall in the east coast region, as around 36% of the second sub-series rainfall fail to be represented by any of the candidate distributions. Overall, only a small percentage (not more than 20%) of the short duration rainfall series do not experience changes of distributions for all three data series.

4.4.1.2 Long Duration Rainfall

Figure 4.6 shows the changes in distributions of long duration rainfall for the five regions. In general, less than 10% of the second sub-series of longer duration rainfall fail to be fitted by candidate distributions for the west coast region.

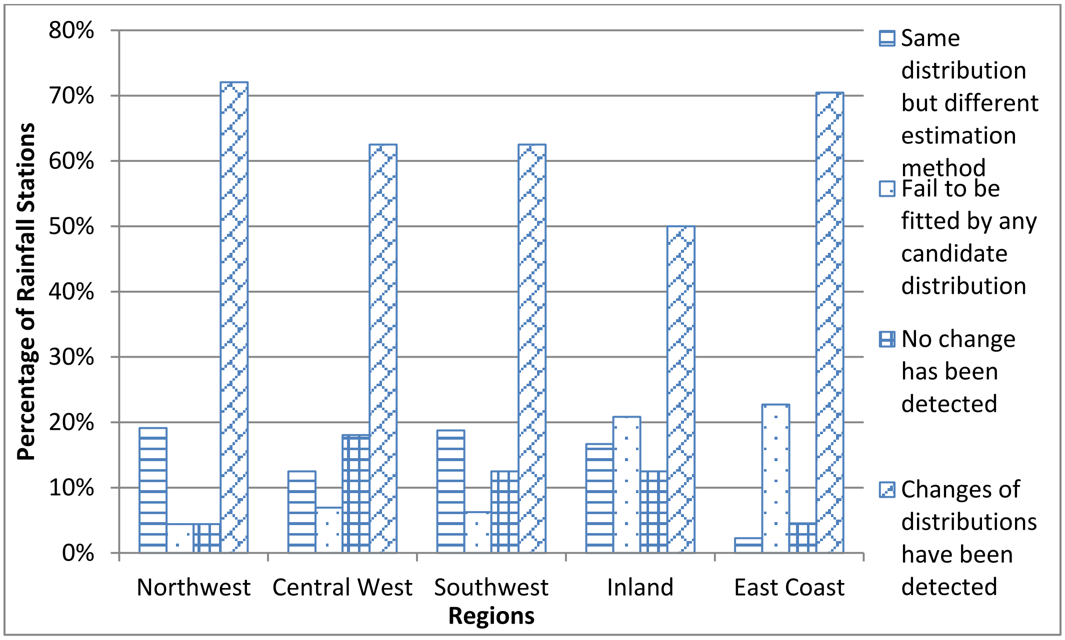

Figure 4.6: Assessment of the changes in rainfall distributions for the five regions (long duration rainfall)

There is a high percentage (no less than 50%) of six-hour to 72-hour rainfall that experienced changes in rainfall distributions. In addition, there is more long duration rainfall series (more than 10% of the data) in the central west, southwest and inland regions compared to the other two regions; do not change in terms of any of the candidate distributions or estimation methods. This coincides with results obtained from the MK trend test in **Section 4.2.4.2**.

4.4.1.3 Discussion

It is insufficient to only analyse the changes in the mean and estimate potential changes in the behavior of extreme rainfall under a scenario of warming climate (Katz & Brown, 1992). Katz & Brown (1992) indicated that extreme events are more sensitive to the variability of climate than average events. In fact, a change in a climate variable will also result in a change in the shape of its distribution (Pall et al., 2015) and different distribution functions or parameter estimation methods may be needed to fit the data.

Generally, the differences between parameter estimates were not large in any case. However, measures of the sample shape parameters are different between the full series and sub-series data thus, different parameter estimation methods are required. (Refer APPENDIX 7 for sample parameter values) Sankarasubramanian & Srinivasan (1999) reveals that the method of moments is preferable at lower skewness for smaller samples, while L-moments are preferable at higher skewness for all sample sizes.

With the year 1995 serving as the change-point in this study, the lengths of first sub-series are in the range of 13 to 24 years, while the length of the second sub-series is 17 years. According to the Interagency Advisory Committee on Water Data (1982) and Lee (2005), a systematic record length with at least 10 years of data is sufficient to ensure that the statistical analysis is viable as a basis for determination. However, Lee (2005) also pointed out that the accuracy of the results could be improved by increasing the number of years of data.

As a result of the changes of distributions in annual maximum rainfall series, statistically derived 100-year rainfall using full series data and sub-series data posterior of the year 1995 was reassessed by comparing the statistically derived 100-year rainfall. Extreme rainfall events are defined as the events in the top one percent (the 99^{th} percentile) of the distribution of annual maximum rainfall (Parzybok et al., 2012). Assessments have been carried out to evaluate the difference between quantiles derived from the sub-periods with those derived from full series for the 100-year return period. In addition, the difference is considered negligible if the discrepancy of the quantiles is less than five percent (5%) throughout the evaluation (Buishand et al., 2010; Mehta & Patel, 2010). Table 4.25 and 4.26 presents the summary of the comparison for the 100-year rainfall obtained from different series data. As the higher priority goes to the more recent rainfall data recorded hence, the comparison of changes in statistically derived 100-year rainfall were made between the full series data and second sub-series data. If the estimated quantiles from the second sub-series is higher than full series, it is denoted as “rise”. Alternatively, if the estimated quantiles from the second series is lower, it is denoted as “fall”. Refer to APPENDIX 6 for the 100-year rainfall from durations of 15 minutes to 72-hour for each delineated region.

Table 4.25: Comparison of the 100-year rainfall for short duration rainfall

Regions	Number of stations							
	15-minute		30-minute		1-hour		3-hour	
	Rise	Fall	Rise	Fall	Rise	Fall	Rise	Fall
Northwest	5	3	4	3	5	3	2	9
Central West	0	6	4	4	12	4	7	2
Southwest	2	0	1	0	2	1	2	0
Inland	2	1	1	0	4	1	2	1
East Coast	3	2	3	2	5	0	4	0

Table 4.26: Comparison of the 100-year rainfall for long duration rainfall

Regions	Number of stations							
	6-hour		12-hour		24-hour		72-hour	
	Rise	Fall	Rise	Fall	Rise	Fall	Rise	Fall
Northwest	5	8	4	5	9	5	8	2
Central West	6	4	4	4	7	4	6	3
Southwest	0	2	0	3	0	3	1	3
Inland	2	2	2	1	1	1	2	1
East Coast	3	1	4	2	5	1	5	3

According to the summary of the results shown in Table 4.25 and 4.26, the estimate quantiles derived from the second sub-series are consistently higher compared to full series data except for:

i. 3-hour to 12-hour rainfall in the northwest region
ii. sub-hourly and 12-hour rainfall in the central west region
iii. 6-hour and 1-day rainfall in the inland region
iv. 6-hour to 3-day rainfall in the southwest region.

The outcome of estimated quantiles depends on the selected candidate distributions, skewness and kurtosis of the series data. In general, higher estimations from second sub-series are related to their sample statistical parameters. Table 4.27 displays the estimated quantiles of full series and sub-series of 15-minute rainfall in the northwest region that show a discrepancy of quantiles more than five percent (5%). If the full series and second sub-series fitted by the same distribution function, the estimated quantiles will be higher when the kurtosis and skewness values are higher. Take station 5704055, 6108001, 4311001, 4811075 and 5210069 for example; these stations have similar or the same distribution and the estimated quantiles from the second sub-series data are higher due to higher skewness and kurtosis values. On the other hand, the comparison cannot be made if the data have different distributions, for example station 53302003, the full series data is fitted by GEV-MOM while the best fitted distribution for the second sub-series data is LN3-LM.

Table 4:27: Comparison between skewness and kurtosis with the estimated quantiles for full series and second sub-series rainfall

State	Stations	15-minute								Dif. (%)
		Full Series				Second Sub-series				
		Q_{100}	Skew	Kur.	Dist.	Q_{100}	Skew	Kur.	Dist.	
Perlis	6401002	51.9	0.87	1.71	GEV-MOM	43.1	0.20	2.95	GEV-LM	-17%
Kedah	5704055	48.5	0.04	0.26	GEV-LM	54.2	1.13	6.24	GEV-LM	12%
	6108001	64.4	1.02	1.19	GEV-MOM	68.9	1.68	7.67	GEV-MOM	7%
Pinang	5302003	55.8	0.60	0.58	GEV-MOM	46	0.04	2.77	LN3-LM	-18%
Perak	4311001	57.9	-0.01	-0.34	GEV-MOM	65.5	0.98	3.95	GEV-LM	13%
	4811075	46.0	0.41	-0.53	GEV-MOM	50.9	0.55	2.93	EV1-MLM	11%
	5210069	44.5	-0.25	-0.17	GEV-LM	47.3	0.33	3.05	GEV-LM	6%

The positive or larger value of skewness and kurtosis indicates that the distribution has heavier tails and a sharper peak which leads to the greater probability in the occurrence of extreme values. In general, the values of kurtosis from the second sub-series are generally higher compared to full series data based on Table 4.28 and Table 4.29. Refer APPENDIX 7 for sample parameter values.

Table 4.28: The number of stations that have higher skewness and kurtosis values for second sub-series compared to full-series data for short duration rainfall

Regions	Number of stations							
	15-minute		30-minute		1-hour		3-hour	
	Skew	Kurt.	Skew	Kurt.	Skew	Kurt.	Skew	Kurt.
Northwest (17)	11	15	6	15	4	14	5	14
Central West (18)	13	15	11	15	10	16	7	16
Southwest (4)	2	3	2	3	2	3	3	3
Inland (6)	2	5	1	4	6	3	3	5
East Coast (11)	4	6	2	8	5	8	5	8

Table 4.29: The number of stations that have higher skewness and kurtosis values for second sub-series compared to full-series data for long duration rainfall

Regions	Number of stations							
	6-hour		12-hour		24-hour		72-hour	
	Skew	Kurt.	Skew	Kurt.	Skew	Kurt.	Skew	Kurt.
Northwest (17)	6	15	8	14	8	15	10	17
Central West (18)	7	17	7	16	8	13	5	14
Southwest (4)	2	3	0	4	0	3	2	3
Inland (6)	3	5	1	4	1	4	1	4
East Coast (11)	3	7	2	9	5	9	5	9

As a result of frequency analysis using two sub-series data, the amount of data that could not be fitted by any candidate distribution have been substantially reduced relative to that obtained when using full series data as shown in Table 4.30 and 4.31. The non-stationarity of full series data may have weakened the performance of distribution functions and hence, a better fit obtained using the second sub-series confirm the stationarity of the sub-series data.

Table 4.30: The number of stations that can be fitted by any of the candidate distribution functions for short duration rainfall

Regions	Number of stations							
	15-minute		30-minute		1-hour		3-hour	
	Full Series	2nd Series	Full Series	2nd Series	Full Series	2nd Series	Full Series	2nd Series
Northwest (17)	13	15	14	15	15	16	17	15
Central West (18)	10	14	14	15	16	17	16	18
Southwest (4)	2	4	3	3	3	4	3	4
Inland (6)	3	5	4	3	5	5	5	5
East Coast (11)	6	6	7	7	7	7	8	8

Table 4.31: The number of stations that can be fitted by any of the candidate distribution functions for long duration rainfall

Regions	Number of stations							
	6-hour		12-hour		24-hour		72-hour	
	Full Series	2nd Series	Full Series	2nd Series	Full Series	2nd Series	Full Series	2nd Series
Northwest (17)	17	17	17	16	17	16	16	16
Central West (18)	17	18	16	17	15	16	15	16
Southwest (4)	4	4	4	4	3	3	4	4
Inland (6)	5	5	4	4	5	5	4	5
East Coast (11)	7	8	7	8	8	9	10	9

4.4.2 Calibration and Validation

From the results of previous section, different combinations of distribution functions and parameter estimation methods have been selected to fit the observed rainfall series. However, some consistencies are found in the results, for example, the same class of probability distribution functions provides an adequate fit to data from the same region. This suggests that some classes of distribution functions are representative of most rainfall data associated to a particular region.

Calibration and validation processes are performed in tandem, known as a cross-validation process. The cross-validation was used for all the samples in the calibration set for the validation process as well to quantify the uncertainty of the regional model for ungauged sites using all considered rain stations (29 stations). These 29 stations are selected because these stations are part of the data series that gave a better representation of the rainfall series for each delineated region and can be modelled by a combination of one of the candidate distributions and parameter estimation methods.

Following the previous section, we have found that the statistical character of the second sub-series significantly differs from the full series data. This highlights the importance of studying the distribution of the second sub-series.

Table 4.32 shows the 29 rainfall stations adopted for calibration and validation processes for both short and long duration rainfall series. The results of the frequency analysis for the second sub-series show that there are some potential distribution functions that can be identified as a regional distribution for each region.

Table 4.32: Rainfall stations adopted for calibration and validation processes (short and long duration rainfall series)

Region	Rainfall Stations			
	Short Duration		Long Duration	
Northwest	5806066	5808001	6401002	5808001
	5302001	5402002	5704055	5402001
	4209093	4708084	5302003	4409091
	4409091	5210069	4311001	4708084
	4811075		4511111	
Central West	3118102	2917001	2917001	3117070
	3411017	3516022	3118102	3411017
	3613004	3710006	3416002	3710006
	3116003	3217003	3217001	3217002
	2719001	2224038	2719001	3217003
Southwest	1437116	1534002	1534002	2025001
Inland	4819027	3121143	3121143	3818054
	2330009		2330009	
East Coast	5428001	5428002	4929001	5331048
	3231163	2235163	5428001	5428002
	1839196		2235163	

4.4.2.1 Short duration rainfall

Figure 4.7- 4.11 show the results of frequency analysis with the combination of best fitted distribution function and parameter estimation method for each region using the 29 calibration data sets.

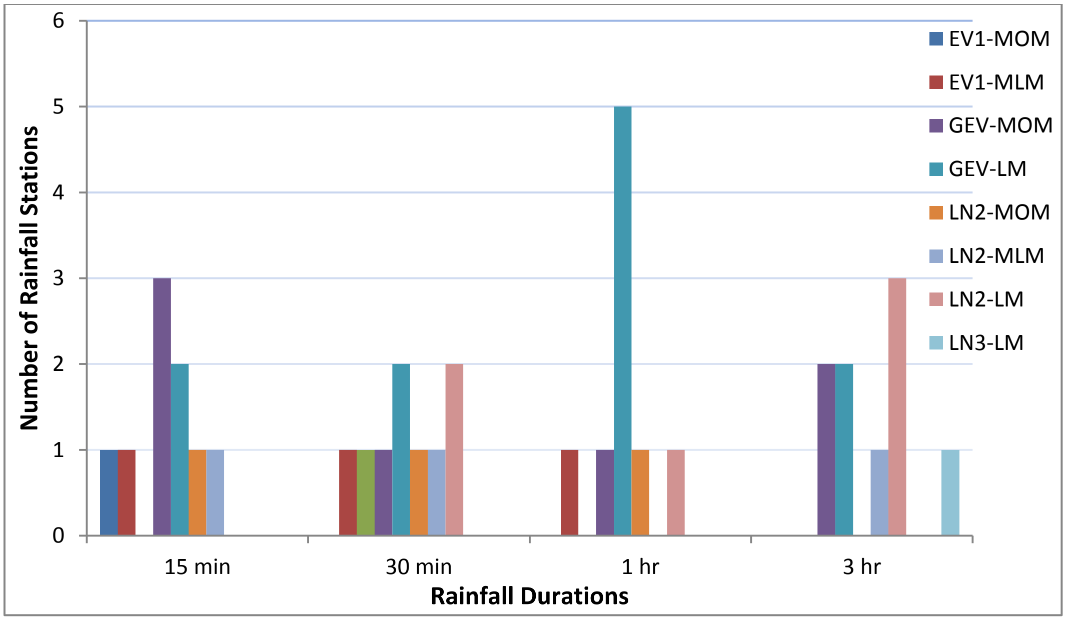

Figure 4.7: Results of the frequency analysis for calibration data across the northwest region (short duration rainfall)

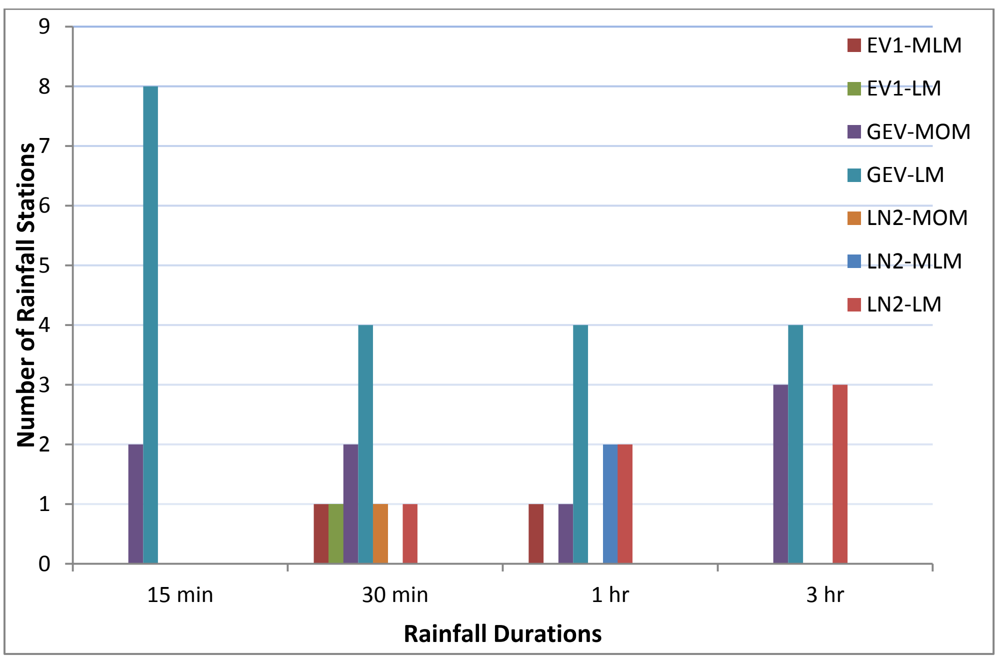

Figure 4.8: Results of the frequency analysis for calibration data across the central west region (short duration rainfall)

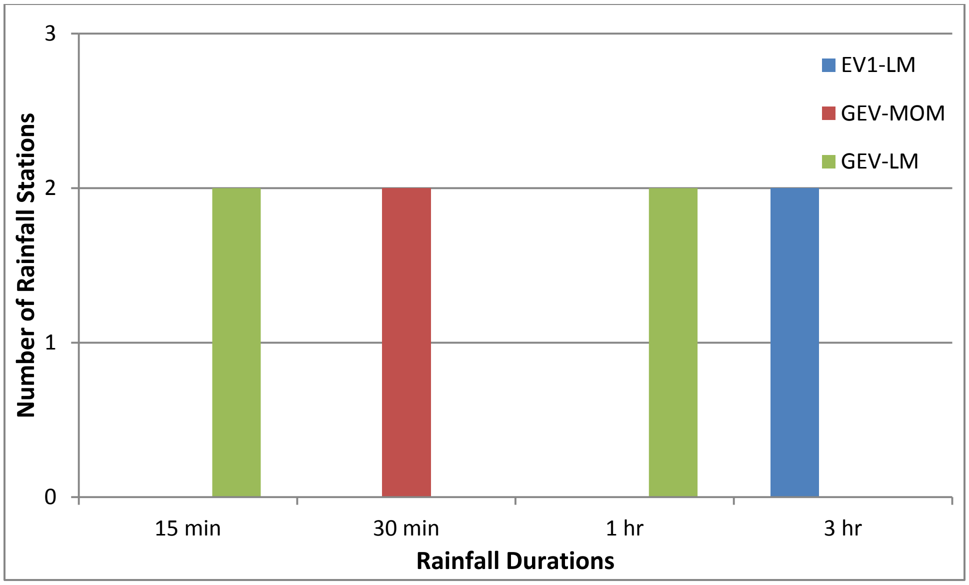

Figure 4.9: Results of the frequency analysis for calibration data across the southwest region (short duration rainfall)

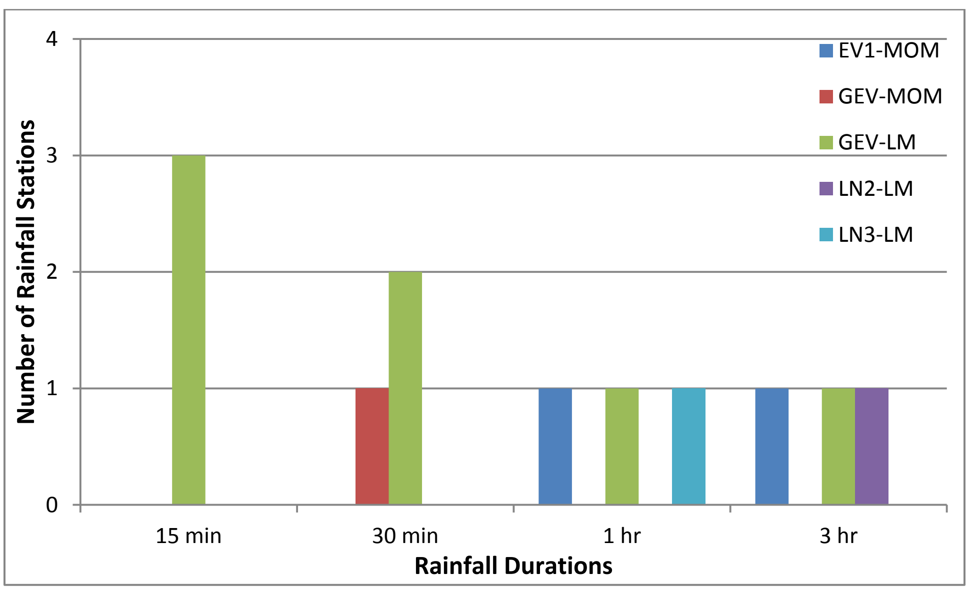

Figure 4.10: Results of the frequency analysis for calibration data across the inland region (short duration rainfall)

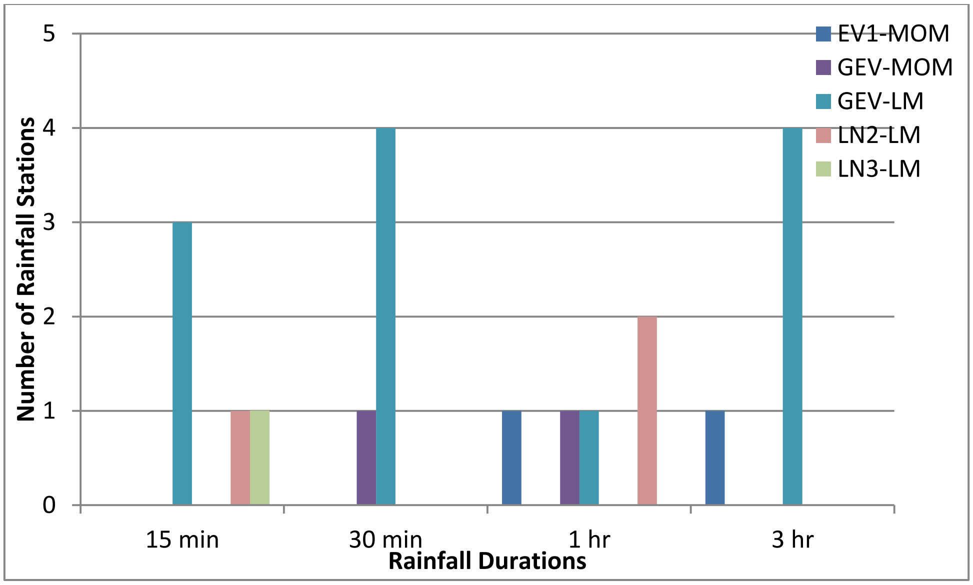

Figure 4.11: Results of the frequency analysis for calibration data across the east coast region (short duration rainfall)

The results (Figure 4.7 to 4.11) show that 85% of the short duration rainfall series across all the regions can be fitted by GEV and LN2 distributions based on the assessment criteria mentioned in Section 3.1.1.4. Table 4.33 shows the number of stations fitted by GEV and LN2 distributions for short duration rainfall series.

Table 4.33: Rainfall series fitted by GEV and LN2 distributions for short duration

Regions	15-minute	30-minute	1-hour	3-hour	Total
Northwest	7/9	7/9	8/9	8/9	30/36
Central west	10/10	8/10	9/10	10/10	37/40
Southwest	2/2	2/2	2/2	0/2	6/8
Inland	3/3	3/3	1/3	2/3	9/12
East coast	4/5	5/5	4/5	4/5	17/20
				Total	99/116 ≈ 85%

On the other hand, the LN3 and LP3 distributions did not fit the observed short duration rainfall most of the time (less than 3% of the rainfall series).

Figure 4.12 to 4.16 are the L-moments ratio diagrams that have been applied to verify the suitability of the distributions identified in the frequency analysis with the short duration rainfall data from 29 stations. Refer to APPENDIX 8 for the value of L-skewness and L-kurtosis. The values of L-Skewness and L-Kurtosis for the candidate distributions are from Rao & Hamed (2000).

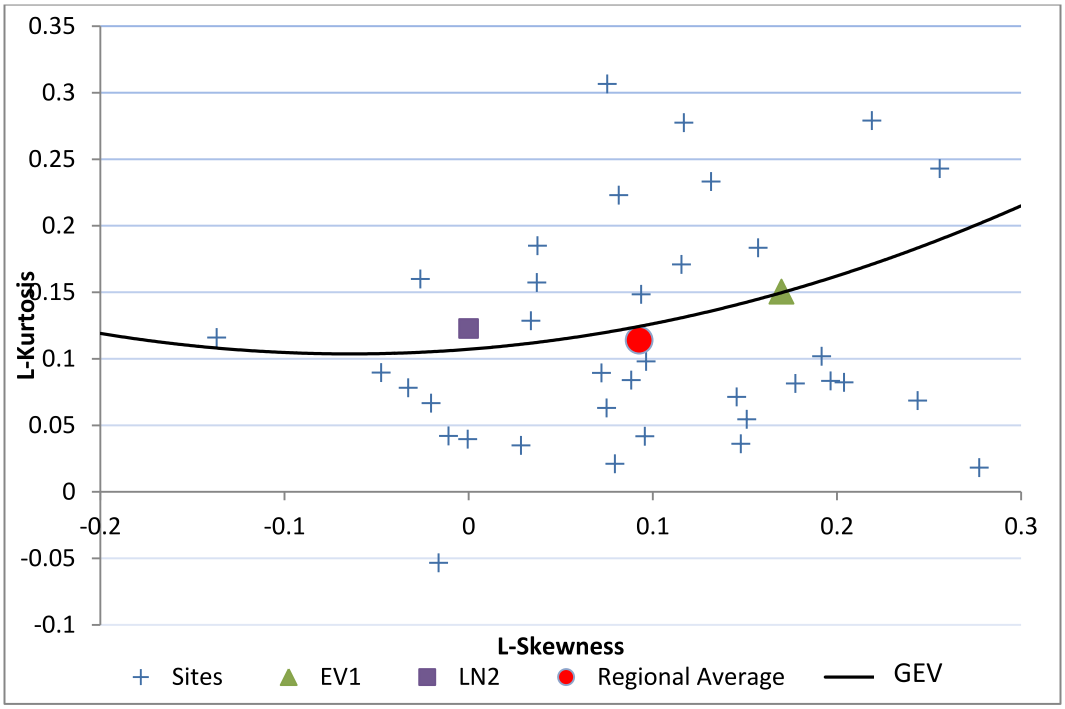

Figure 4.12: L-moments ratio diagram for the northwest region (short duration rainfall)

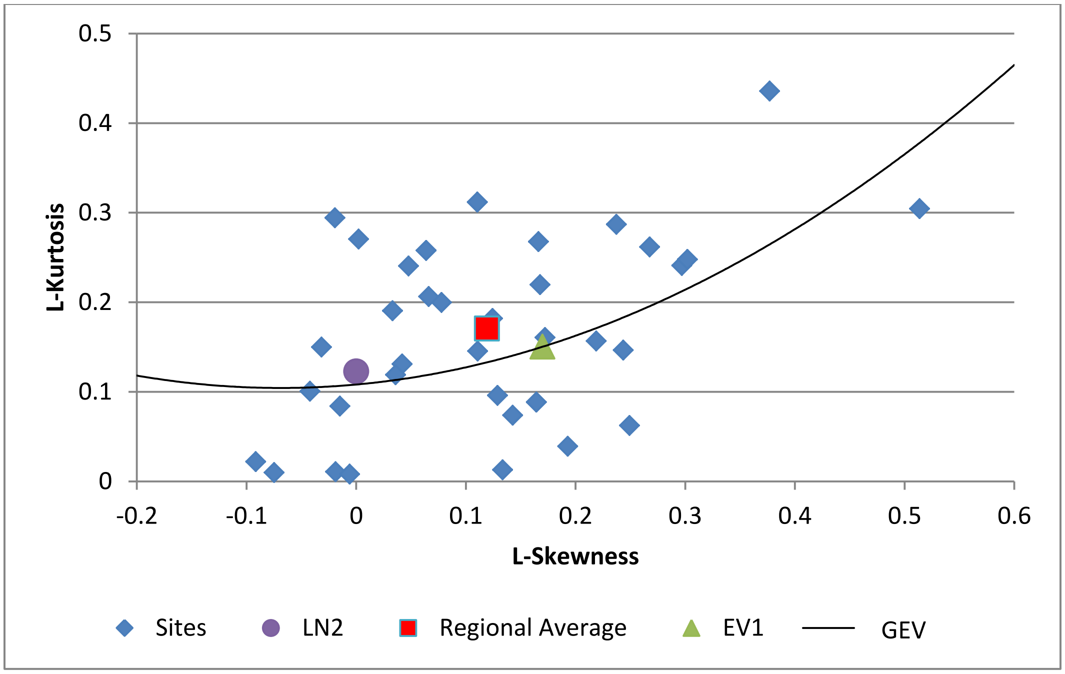

Figure 4.13: L-moments ratio diagram for the central west region (short duration rainfall)

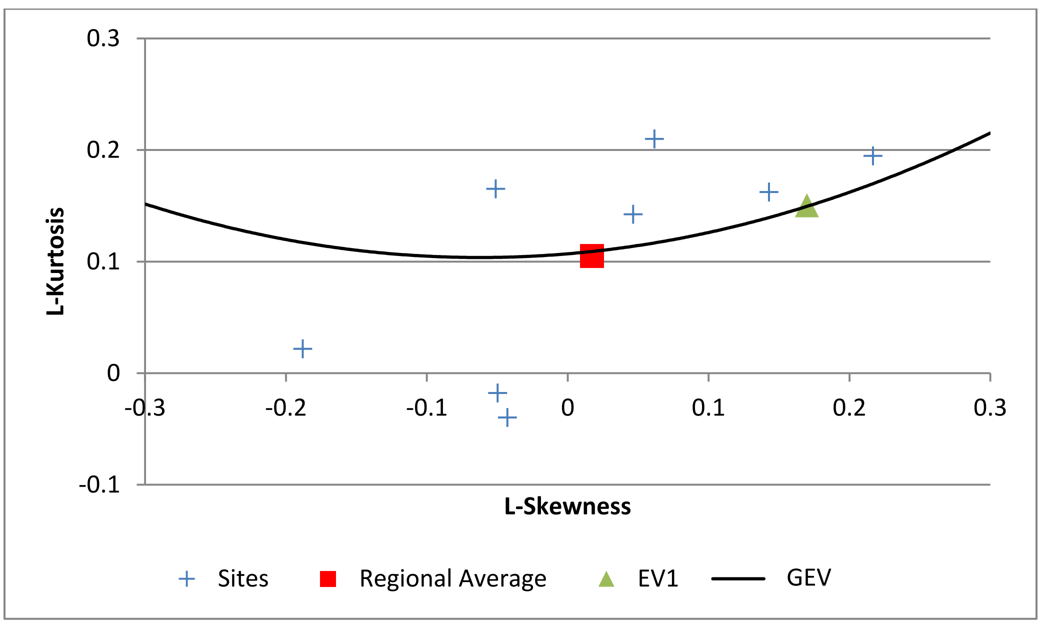

Figure 4.14: L-moments ratio diagram for the southwest region (short duration rainfall)

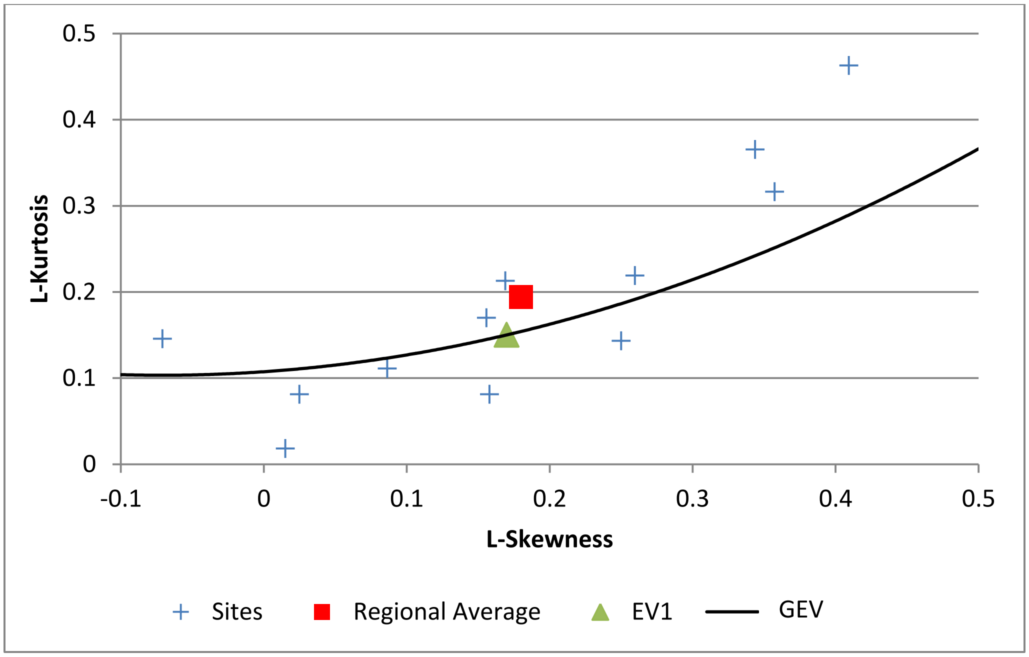

Figure 4.15: L-moments ratio diagram for the inland region (short duration rainfall)

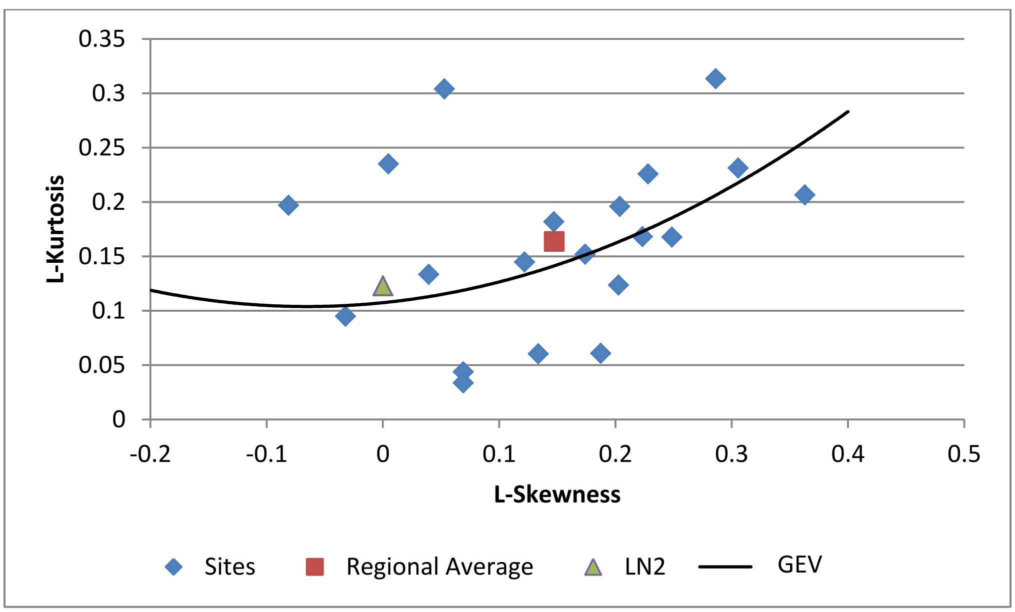

Figure 4.16: L-moments ratio diagram for the east coast region (short duration rainfall)

4.4.2.2 Long duration rainfall

The results of frequency analysis with long duration rainfall using only the second sub-series data are shown in Figure 4.17 –4.21. From the results shown, the best fitted combination of distribution function and parameter estimation method for the northwest and central west regions are less specific compared to the other regions for long duration rainfall.

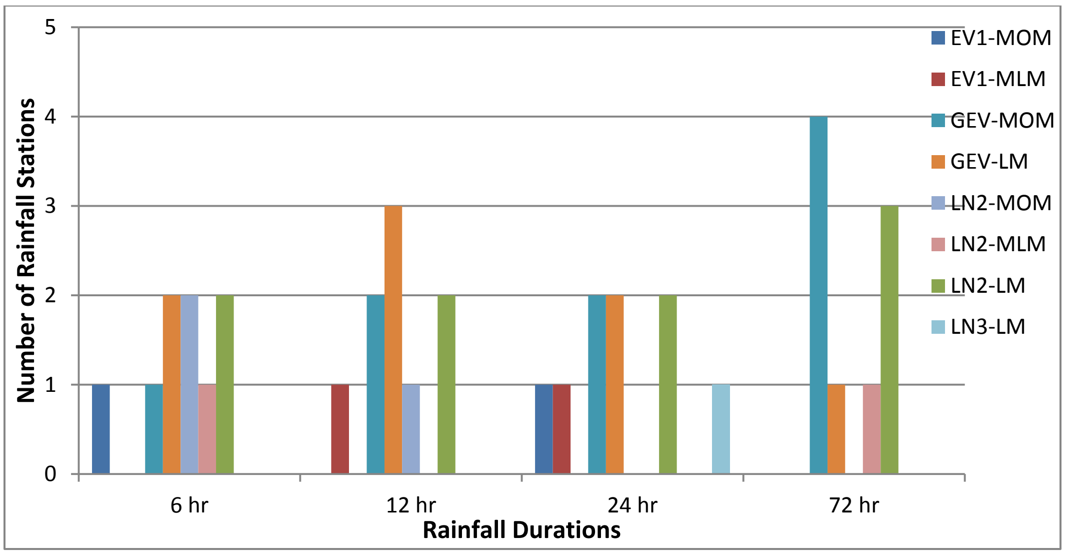

Figure 4.17: Results of the frequency analysis for calibration data across the northwest region (long duration rainfall)

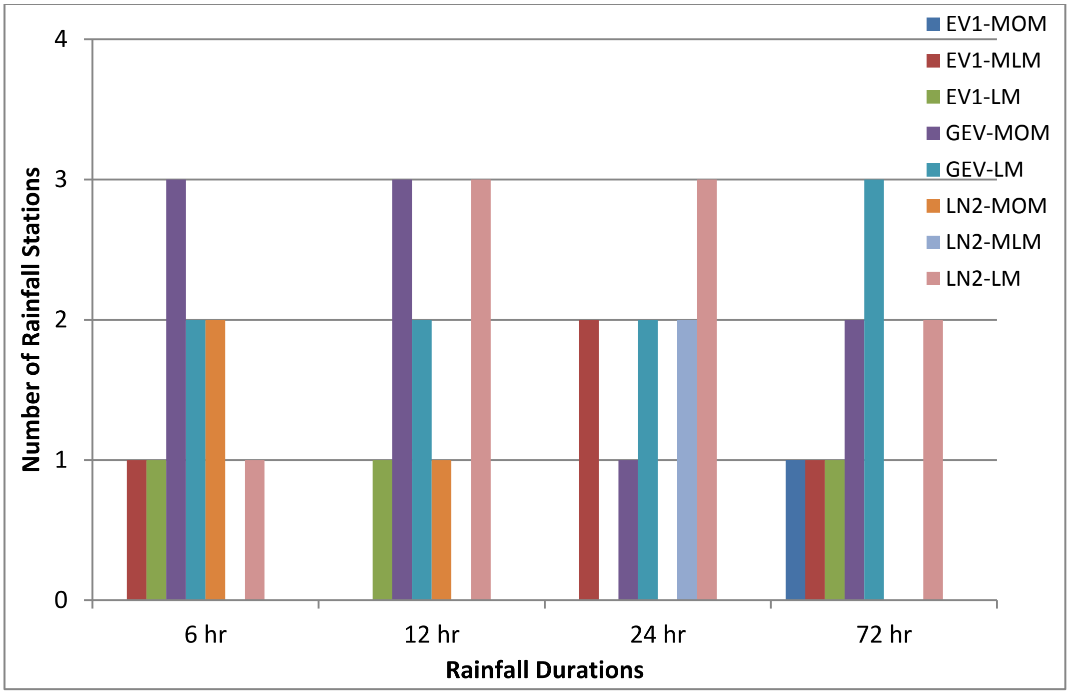

Figure 4.18: Results of the frequency analysis for calibration data across the central west region (long duration rainfall)

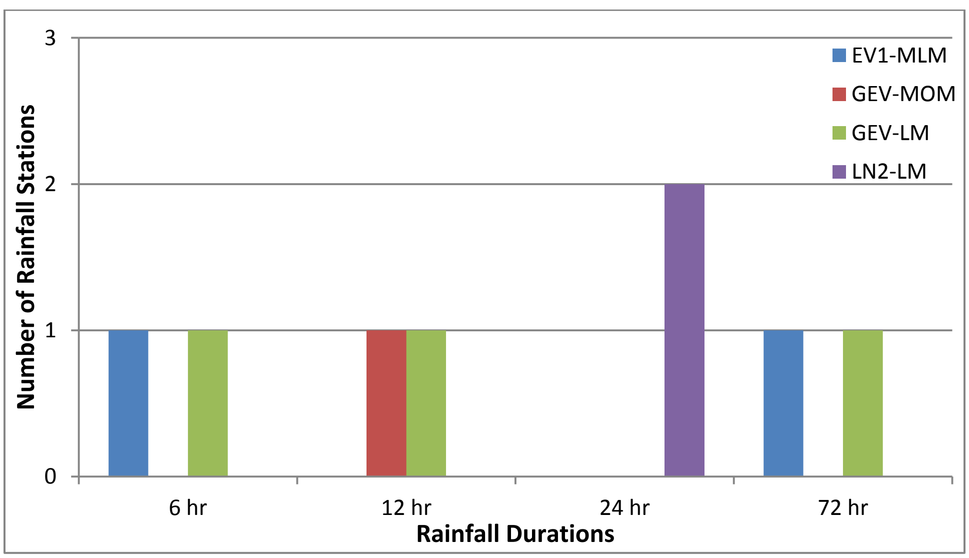

Figure 4.19: Results of the frequency analysis for calibration data across the southwest region (long duration rainfall)

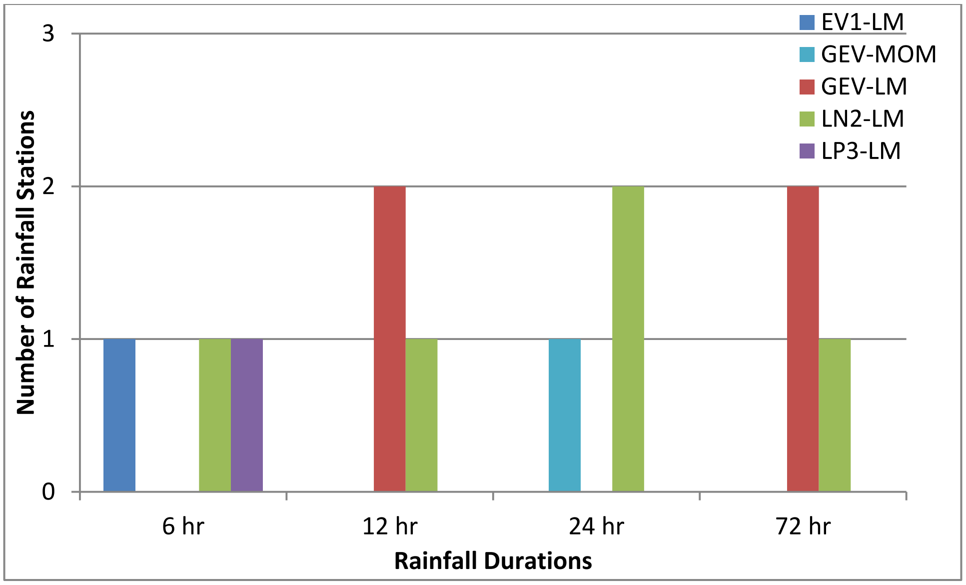

Figure 4.20: Results of the frequency analysis for calibration data across the inland region (long duration rainfall)

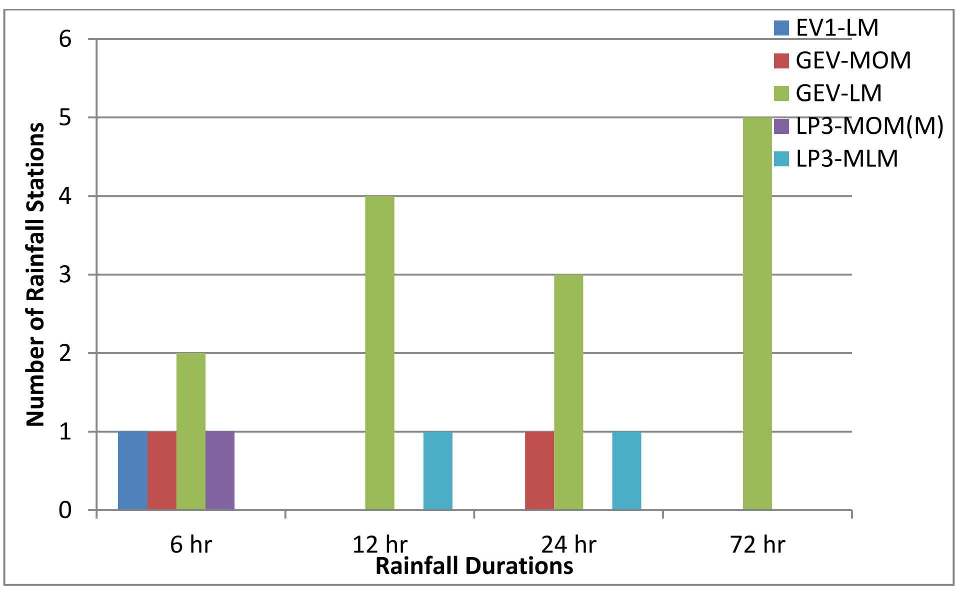

Figure 4.21: Results of the frequency analysis for calibration data across the east coast region (long duration rainfall)

Similar to the short duration rainfall series, GEV and LN2 distributions are able to fit over 82% of the long duration rainfall data. The results presented in

Figure 4.17-4.21 imply that LN2 is comparably robust to the GEV distribution in the northwest and central west regions, and it is even more robust for the inland region (long duration rainfall). Table 4.34 shows the number of stations fitted by GEV and LN2 distributions for long duration rainfall.

Table 4.34: Rainfall series fitted by GEV and LN2 distributions for long duration

Regions	6-hour	12-hour	1-day	3-day	Total
Northwest	8/9	8/9	6/9	9/9	31/36
Central west	8/10	9/10	8/10	7/10	32/40
Southwest	1/2	2/2	2/2	1/2	6/8
Inland	1/3	3/3	3/3	3/3	10/12
East coast	3/5	4/5	4/5	5/5	16/20
				Total	95/116 ≈ 82%

The results indicate that the EV1, LN3 and LP3 distributions are not fit to be selected as regional distribution functions to represent any delineated region. The L-moments ratio diagrams shown in Figure 4.22 to 4.26 provide a visual assessment on the fitness of the distribution function. Refer to APPENDIX 8 for the value of L-skewness and L-kurtosis. The values of L-Skewness and L-Kurtosis for the candidate distributions are from Rao & Hamed (2000).

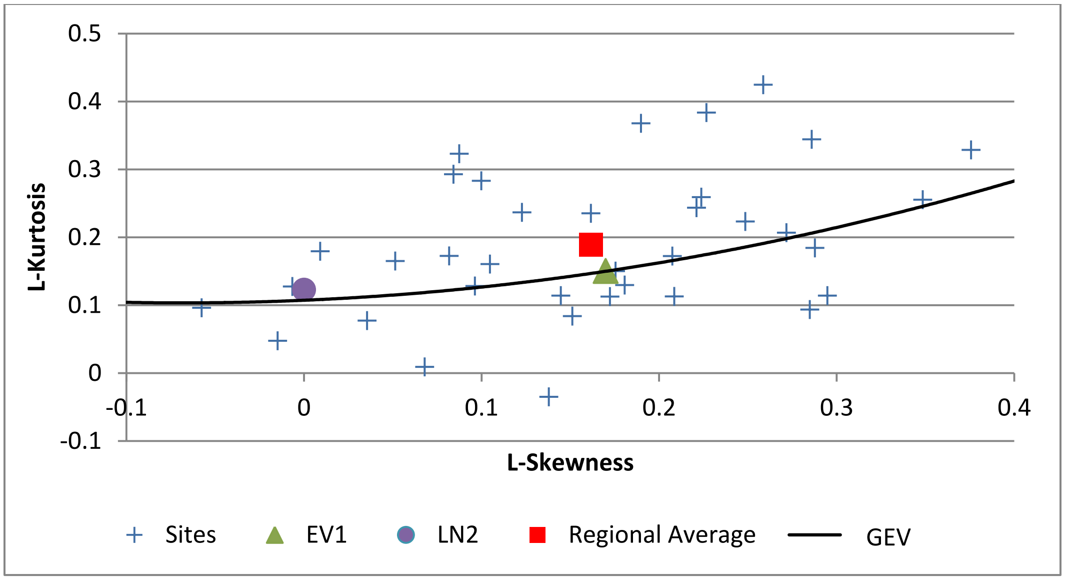

Figure 4.22: L-moments ratio diagram for the northwest region (long duration rainfall)

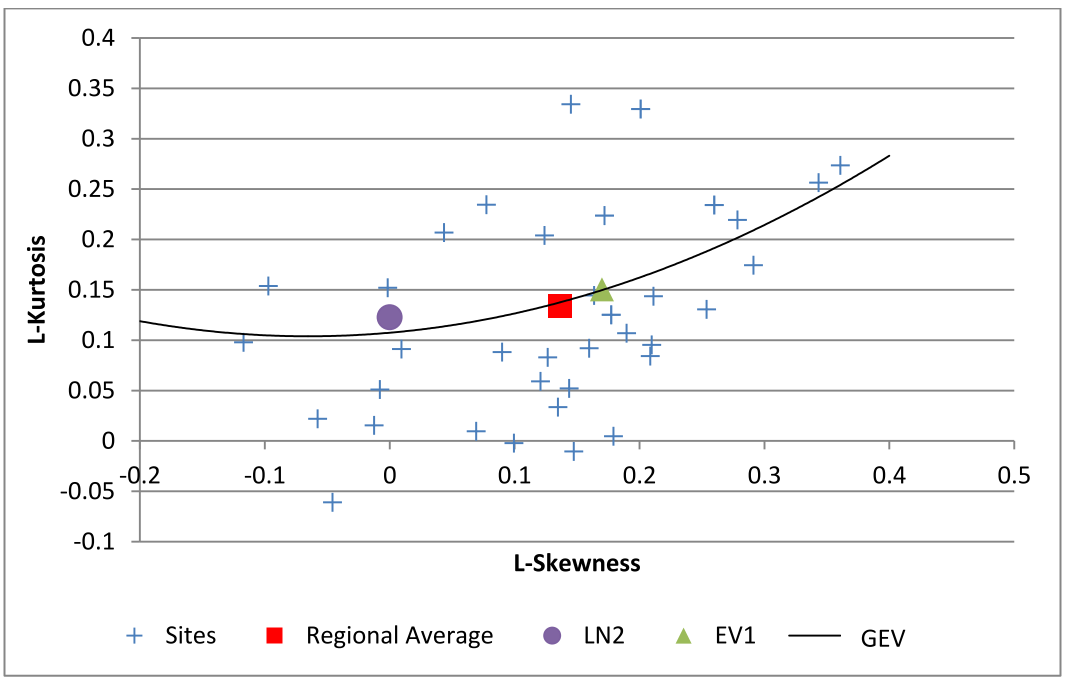

Figure 4.23: L-moments ratio diagram for the central west region (long duration rainfall)

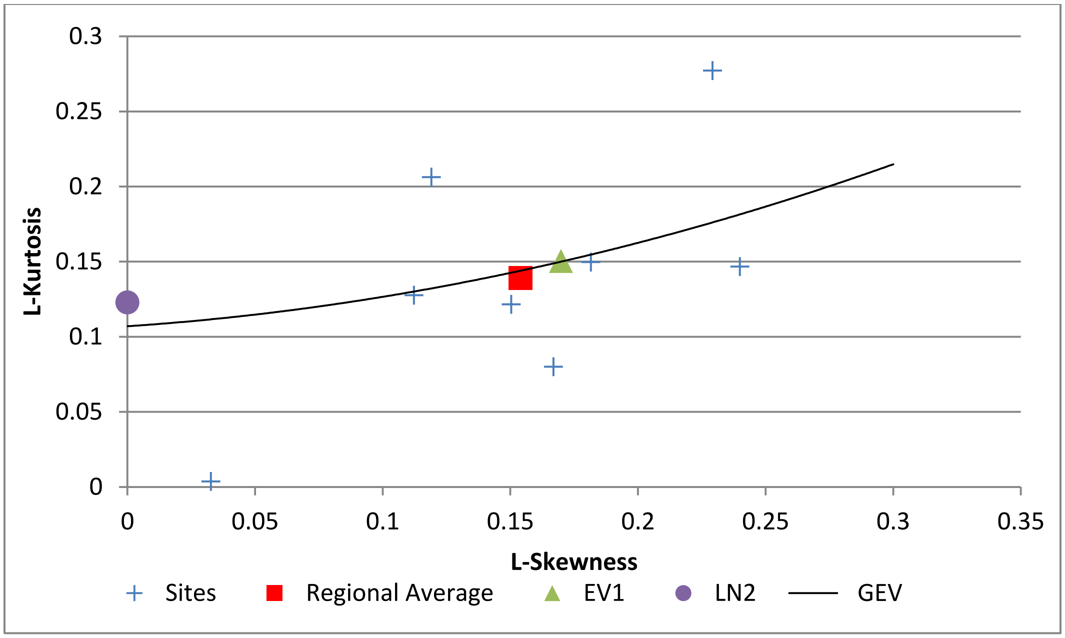

Figure 4.24: L-moments ratio diagram for the southwest region (long duration rainfall)

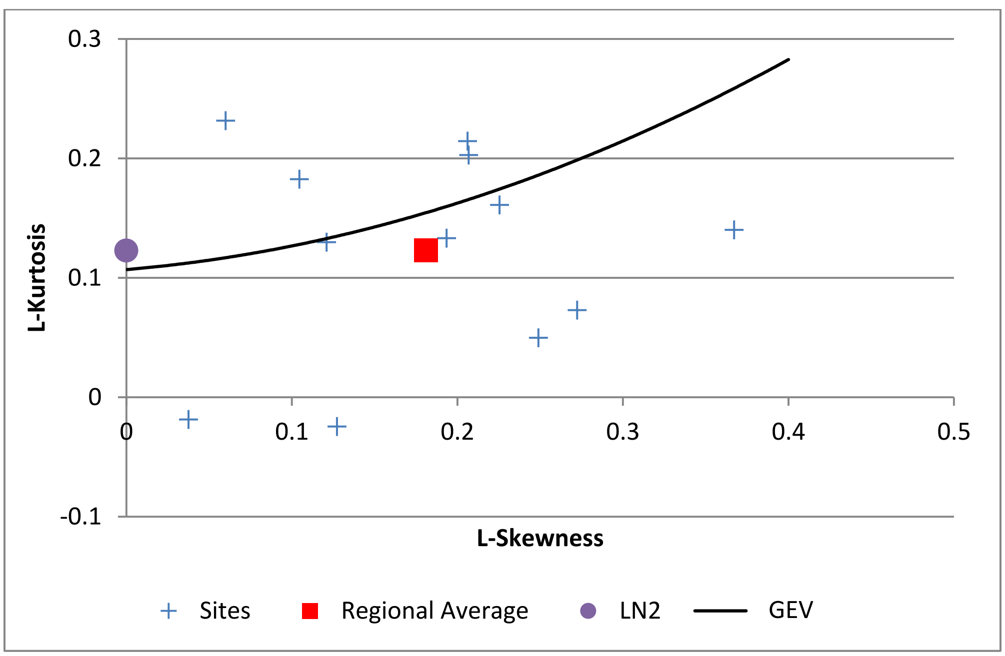

Figure 4.25: L-moments ratio diagram for the inland region (long duration rainfall)

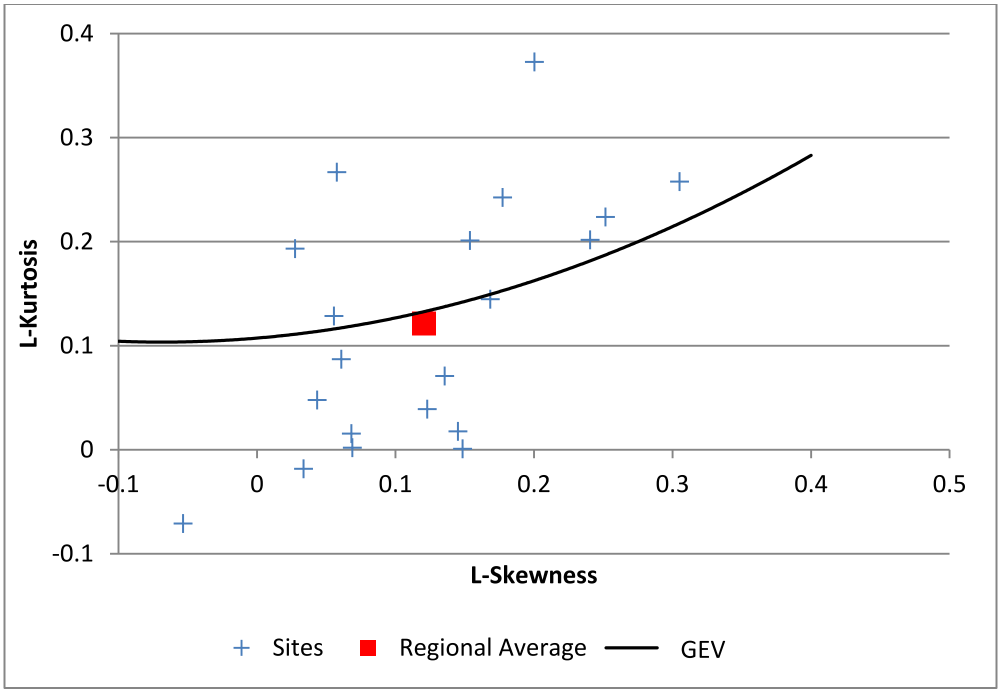

Figure 4.26: L-moments ratio diagram for the east coast region (long duration rainfall)

4.4.2.3 Discussion

From the L-moments ratio diagrams, the sample L-moment ratios estimated from the observations of each delineated region do not follow the theoretical curve and points of the candidate distributions and hence, is hard to ascertain a suitable distribution for the delineated region. Even though the use of the L-moments ratio diagram is recommended in identifying regional frequency distribution (Vogel & Fennessey, 1993; Peel et al., 2001), alternative methods are recommended to validate the candidate distributions. In this case, Mishra et al. (2009) suggested that conventional frequency analysis should be applied to the data sets in each region. The distribution function which gives an adequate fit to most of the stations in the region are selected as the regional frequency distribution.

Figure 4.27 to 4.31 present the outcomes of the analysis based on recommendations by Mishra et al. (2009).

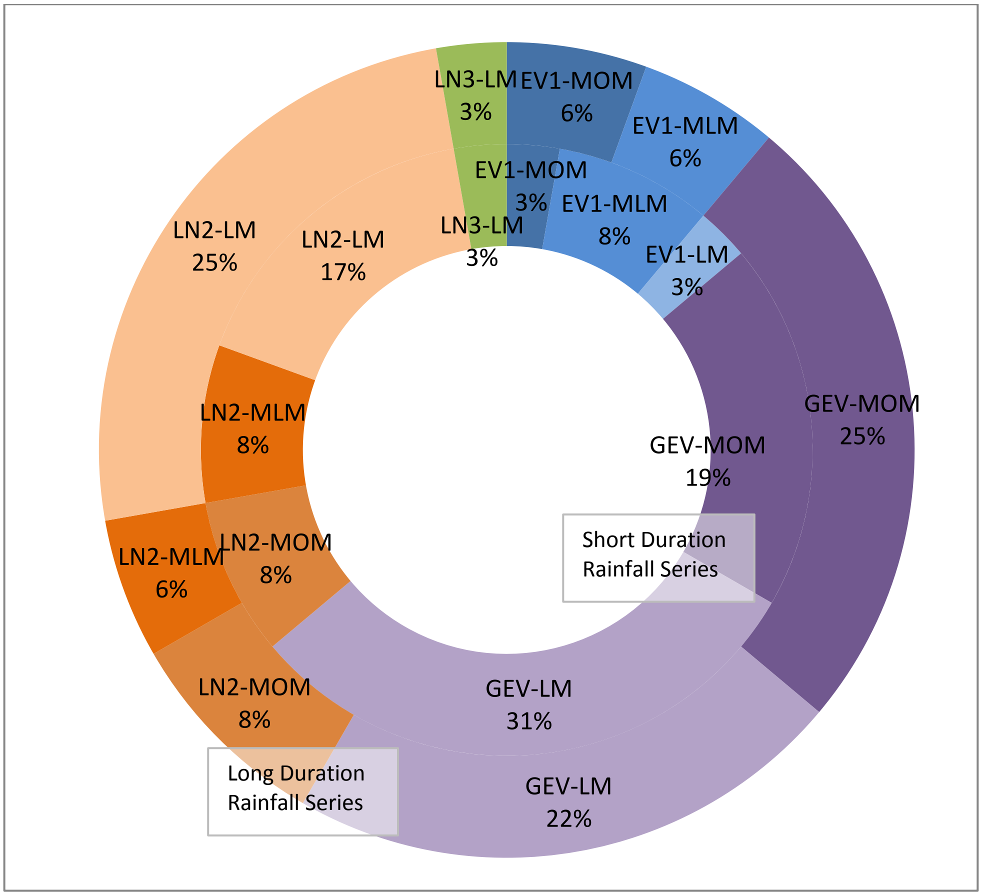

Figure 4.27: Distribution functions that best fitted the calibration and validation data across the northwest region for both short and long duration rainfall

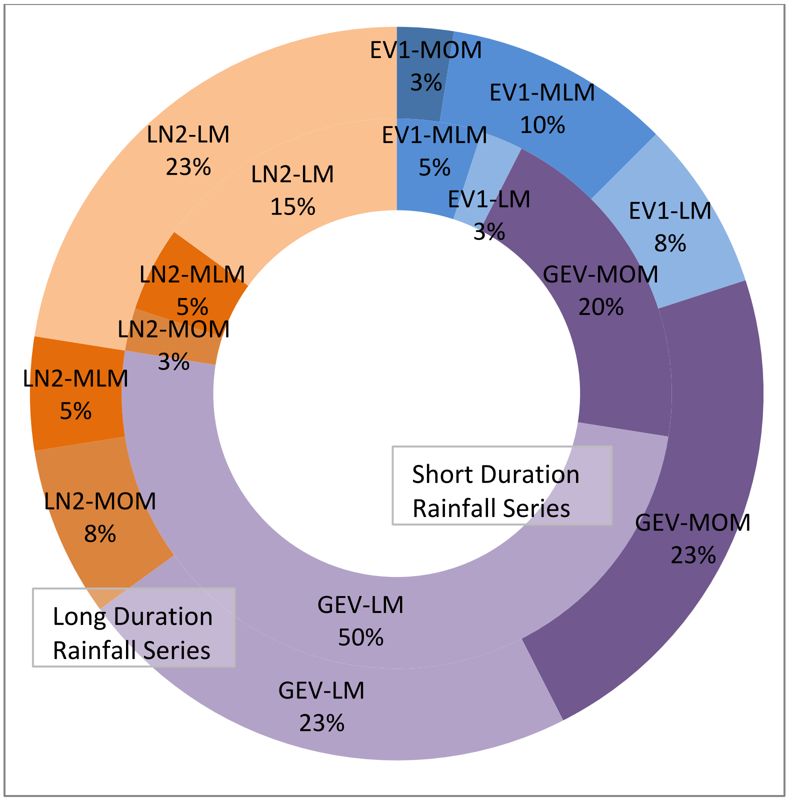

Figure 4.28: Distribution functions that best fitted the calibration and validation data across the central west region for both short and long duration rainfall

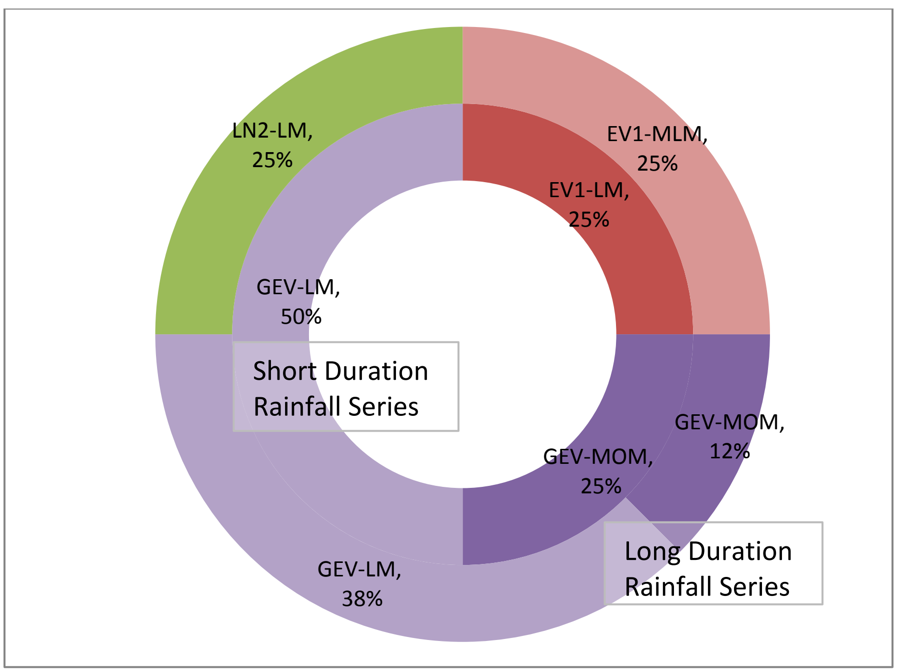

Figure 4.29: Distribution functions that best fitted the calibration and validation data across the south west region for both short and long duration rainfall

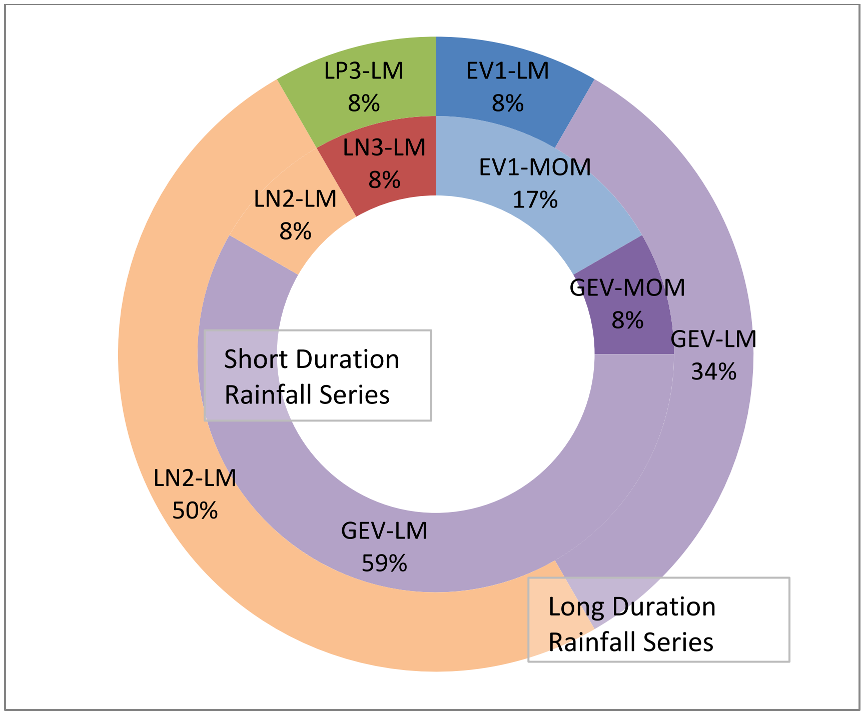

Figure 4.30: Distribution functions that best fitted the calibration and validation data across the inland region for both short and long duration rainfall

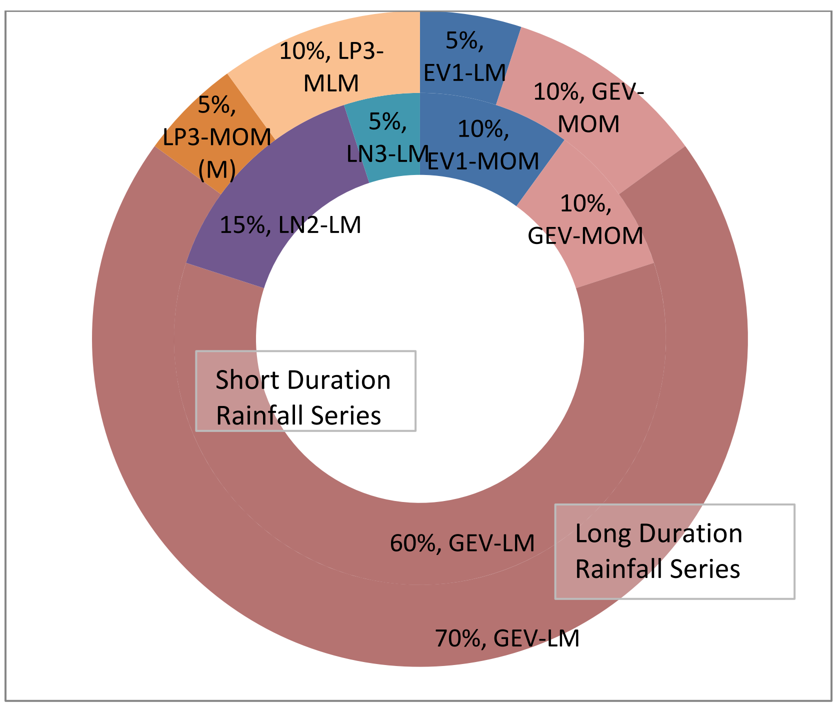

Figure 4.31: Distribution functions that best fitted the calibration and validation data across the east coast region for both short and long duration rainfall

From Figure 4.27 to 4.31, it can be concluded that the GEV distribution fitted most of the calibration and validation data for both short and long duration rainfall in all regions, followed by the LN2 and EV1 distributions. Furthermore, the GEV distribution not only outperforms other distributions by fitting 50% (Northwest) to 75% (Southwest) of the short duration rainfall data but also does well in fitting 42% to 80% of the long duration rainfall series especially in the east coast region (80% of the rainfall). However, the performance of GEV is less dominant in long duration rainfall compared to short duration rainfall as the performance of the LN2 distribution is found to be comparable to the GEV distribution in the northwest and central west regions. In addition, the performance of the LN2 distribution shows better fits for long duration rainfall in the inland region.

Overall, the reason for why GEV appears to outperform other distributions is because the distinctive shape parameter (κ) of GEV distribution that governs the tail behaviour of the distribution and hence, gives a better fit to satisfy both the short and long duration rainfall data series.

In this study it was found that the LN3 and LP3 distributions do not fit the rainfall series well. From the literature, these distributions are typically used to describe flood flow data most of the time (Chin, 2000; Vogel et al., 1993; Borujeni & Sulaiman, 2009).

Table 4.35 shows the proposed regional distribution functions and the corresponding parameter estimation methods for each hydrologic region. The order of the distribution functions and parameter estimation methods (for example, GEV-LM) shown in Table 4.35 indicates the percentage of the stations fitted by the combination.

Table 4.35: Proposed distribution functions and parameter estimation methods for each delineated region and rainfall series

Regions	Short Duration Series	Long Duration Series
North-west	GEV-LM, GEV-MOM, LN2-LM	GEV-MOM, LN2-LM, GEV-LM
Central West	GEV-LM, GEV-MOM, LN2-LM	GEV-LM, LN2-LM, GEV-MOM
South-west	GEV-LM, GEV-MOM	GEV-LM, LN2-LM, EV1-MLM
Inland	GEV-LM, EV1-MOM	LN2-LM, GEV-LM
East Coast	GEV-LM	GEV-LM, LN2-LM

Note: GEV is the Generalised Extreme Value distribution, LN2 is the two-parameter lognormal distribution, EV1 is the Extreme Value Type 1 distribution; LM is the L-moments method and MOM is the method of moments.

From Table 4.35, the L-moment method is preferred compared to method of moments and maximum likelihood methods. The L-moment method is more robust in adapting to a wider range of distributions and is more accurate for small samples according to Hosking (1990). On the other hand, the performance of the maximum likelihood method is not satisfactory because the maximum likelihood estimators do not always exist for large samples (In, 2003).

4.5 SUMMARY OF MAIN FINDINGS

The main findings with regards to the hydrologic statistical assessment on the rainfall series are summarised as follows:

- The northwest, and more importantly, the urbanised central west regions have experienced an increase in rainfall during the northeast monsoon. Usually the northeast monsoon brings a large amount of rainfall to the east coast region; however, the result shows that the northeast monsoon is strengthening over the west coast regions as well. The significant increasing trend also been noticed in short duration annual maximum rainfall series at the 10% significance level. In the east coast region, 54.5% of the northeast monsoon rainfall show significant increasing trends and the short duration rainfall also shows significant increasing trends as well. More importantly, the short, high-intensity rainfalls are often associated with flash floods that occur locally (floods produced by short-duration rainfall are often referred to as “flash” floods) (Georgakakos, 1986; Marchi et al., 2010). Flash floods are often more hazardous than slower-onset floods because of the difficulty in providing sufficient time for dissemination of warning messages (Ahern et al., 2005). This study shows that the greatest increases occur in short-duration rainfall during the northeast monsoon, potentially leading to an increase in the magnitude and frequency of flash floods.
- Overall, few stations show significant change in trend for long duration rainfall trend except for the central west region, as the significant increasing trends detected are more noticeable compared to other regions such as northwest, southwest, inland and east coast regions. The monsoon often leads to heavy rainfall events that last for longer periods thus, the

daily or multi-day rainfall data are used in the studies of monsoon rainfall (Svensson & Berndtsson, 1996; Suhaila et al., 2010). The significant increasing trend detected in long duration rainfall could be related to the intensification of monsoon rainfalls along with the significant increasing trend detected during the northeast monsoon. All these indications (increase in both short and long duration rainfall) show that the central west region is exposed to higher flood risk than other regions.

- By assuming the year 1995 is the beginning of the change in trend, the annual maximum rainfall series has been divided into two sub-series using 1995 as the cutting point. The results of frequency analysis using both sub-series data show that changes in distributions have developed, as different combinations of distribution functions and parameter estimation methods are required to give the best fit to full series data and both sub-series data of any duration and station.
- As a result of the changes in distributions detected, estimated quantiles from most of the regions are higher (more than 5% difference) when the second sub-series data are used compared to full series data. For 47% (16/34) of northwest, 59% (23/39) of central west, 88% (7/8) of southwest, 75% (9/12) of inland and 79% (15/19) of east coast short duration rainfall have higher estimated quantiles from Table 4.25. While for long duration rainfall, 57% (26/46) of northwest, 61% (23/38) of central west, 8% (1/12) of southwest, 58% (7/12) of inland, 71% (17/24) of east coast regions have higher estimated quantiles from Table 4.26.

Moreover, based on the frequency analysis using two sub-series data, the amount of data that could not be fitted by any candidate distribution has been substantially reduced as discussed in Section 4.4.1.3.

- Based on the calibration and validation data sets, even though all rainfall events cannot be fitted by a specific distribution function, the GEV distribution performed better than alternative candidate distribution functions in representing the second sub-series data in all the regions except for long duration rainfall in the inland region (only 33% of inland rainfall represented by GEV). To be more precise, the combination of GEV and L-moments is more robust and is able to give an adequate fit to most of the data.

4.6 CONCLUSIONS

The results from these hydrologic statistic methods gives a better understanding of the change of rainfall pattern in terms of spatial and temporal variations, and the impacts on the hydrologic frequency analysis procedure.

The MK trend test results identified the significant trend in both increasing and decreasing direction present in different types of rainfall data. However, failing to detect significant changes implies that there is insufficient evidence to conclude that the trend existed (instead of saying that no trend is existed). The MK trend test results are summed up as follows:

- 82% of the annual rainfall experienced an increasing trend but only 43% of the data show significant trend with the largest increases in the central west region. Significant decreasing trend is only observed in the southwest region.
- More substantial change in rainfall pattern was detected during the northeast monsoon than southwest monsoon especially in the central west region.
- The number of significant increases is greatest in short duration rainfall range from 15-minute to three-hour rainfall in most of the regions except the southwest region.
- No substantial changes were discovered in the inland region. The significant increasing trend was only observed in 15- and 30-minute annual maximum rainfall series for this region.
- Around 36% (4/11) of the annual rainfall and more than 50% (6/11) of the northeast monsoon rainfall in the east coast region shows a significant increasing trend.

The non-stationarity detected in the MK test is further validated by Mann Whitney and, Mood's median tests. By using the year 1995 as the change-point, results reveal that the number of stations that show significant non-stationarity is greatest in the short duration annual maximum rainfall for the central west region. Furthermore, the results from non-stationary tests and the MK test are fairly coherent. In addition, spatial and temporal variability of rainfall is detected, it is necessary to analyse the rainfall pattern by dividing the study area into regions according to geographical characteristics and degree of urbanisation.

From the outcome of frequency analysis, the performance of the distribution function and parameter estimation method in fitting the rainfall data have improved when only the second sub-series are used for both short and long duration. Since the performance of distribution functions is better with the truncated second sub-series, this suggests that the assumption of stationarity is valid. When the full series data was used, around 24% (53/224, 56 stations for four duration) of the short duration rainfall fails to be fitted by any distribution function and the percentage reduced to 17% (38/224) when only second sub-series data is used. While for the long duration rainfall, the fitness of the distribution also improved when the second sub-series data is applied, corresponding to 13% (29/224) of cases failing to be fitted by any distribution function using full series data and reduced to around 11% (24/224).

Hydrologic frequency analysis is used to estimate the frequency and amount of extreme conditions, floods and droughts. Hence, due to different extents of non-stationarity detected among the rainfall series, there is a need to continuously update the combination of probability distribution function and parameter estimation method so as to find the most suitable combination. In order to address the uncertainty of the frequency and magnitude of future changes, it is essential to incorporate the non-stationarity of rainfall data into frequency analyses.

Throughout this study, the analysis results showed that the application of frequency analysis using more current posterior data yields better estimations than conventional approaches. It provides better and more up-to-date results in analysing the effect and characteristics of hydrologic change with more current data. In addition, it is essential to identify the best fitted distribution function and parameter estimation method combination for frequency analysis in every region due to the spatial variability in rainfall series. Although the rainfall data can’t be fitted by a specific distribution, some distribution functions can perform better than others. In this thesis, the combination of GEV and L-moments performed better in representing the second sub-series data in most of the regions.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusions drawn on the research work undertaken and the recommendations made as an outgrowth of this study. This study is about the assessment of hydrologic statistics for rainfall trend and frequency analysis with impacts from climate change in Peninsular Malaysia. The work covered the evaluation and identification of the best combination of probability distribution function and parameter estimation method for frequency analysis; evaluation of changes in rainfall trend using the Mann-Kendall trend test and; detection of trend change-point using non-stationary tests and the Sequential Mann-Kendall test. All these statistical tests were carried out to assess the influence of climate change on rainfall patterns and its effect on frequency analysis and hence, improve the reliability of the magnitude of estimated rainfall.

The current practice in engineering operates on the assumption that rainfall series is stationary. This oversimplification potentially exposes hydraulic structure designs to significant climate change risks. One of the objectives of this thesis is to detect the presence of climate change, assuming that such change manifests as a change in trend and non-stationarity in rainfall series. Specifically, this thesis explores the use of posterior time series in the quantiles estimation since this sub-series appropriately gives the most up-to-date characterization of the rainfall pattern. The methodology proposed has demonstrated some success in the studied cases. It is hoped that future works can extend upon the groundwork established here.

5.1 CONCLUSIONS

The assessment on rainfall series consists of four sections and salient findings of each section are as follow:

1. The purpose of hydrologic frequency analysis when using entire record length of data is to investigate the temporal and spatial variations in rainfall pattern. From the results of the frequency analysis, none of the candidate distribution functions were able to fit the data from all (56) rainfall stations and, none of combinations were able to fit all eight duration rainfall for any one of the 56 stations. Hence, to explore the spatial and temporal characteristic of the extreme rainfall series, the study area has been delineated into five regions and the eight duration annual maximum rainfall have been clustered into two groups which are short- and long-duration rainfall.

   The second finding from this analysis is there are a certain percentage of rainfall data that cannot be fitted by any of the candidate distribution function, especially for short-duration e.g. 39% of 15-minute and 25% of 30-minute rainfall. This could be an indication of the presence of non-stationary “trends” in rainfall data. However, it could be due to the presence of extreme data at the right tail (outliers) as well.

2. Consequently, further study has been carried out to examine whether there are changes in trend of rainfall recorded at various rainfall stations in Peninsular Malaysia using the Mann-Kendall trend test. The most significant increasing trends have been detected in the west coast; predominantly the urbanised central west region followed by the northwest region. For the central west region, 61% of the annual rainfall, 72% of northeast monsoon rainfall and more than 60% of the 30-minute annual maximum rainfall have experienced a significant upward trend. While for the northwest region, 29% of annual rainfall, 65% of northeast monsoon, 41% of the sub-hourly rainfall and 1-hour rainfall has experienced a significant increasing trend. The most substantial decreasing trend was detected in the southwest region where 50% of annual rainfall and 50% of southwest monsoon rainfall have shown a significant decreasing trend.

   While some significant increasing trends have been detected for rainfall series in the east coast region, only 36% of annual rainfall and 54% of northeast monsoon rainfall show significant increasing trend. On the other hand, not much trend is observed in the inland region. The significant increasing trend is only observed in 15-minute and 30-minute rainfall for this region.

   As the presence of trend in the rainfall series indicates the possible presence of non-stationarity in the data hence, two non-stationary tests (Mann-Whitney and, Mood's median tests) were applied with year 1995 as a cutting point (beginning of significant warming trend detected) to ascertain the presence of non-stationarity in the rainfall series. Once again, non-stationary tests results show that non-stationarity in the data was more substantial over the annual rainfall in the west coast regions, ranging from 41% in the northwest to 50% in the southwest and central west regions.

Based on the change-point (year 1995), the non-stationarity in short duration rainfall is more noticeable compared to long duration rainfall especially in the northwest and central west regions. Non-stationarity was detected in nearly 35% of 15-minute rainfall series and more than 47% of the 30-minute and one-hour annual maximum rainfall series in the northwest region. For the central west region, 61% of the 15-minute rainfall series and more than 50% of the 30-minute and one-hour annual maximum rainfall series in the central west region exhibit non-stationarity. While for the inland and east coast regions, the non-stationarity is only noticeable in 15-minute and 30-minute rainfall series.

Overall, changes in trend and the presence of non-stationarity have been detected in the observed rainfall series across the study area especially in the west coast region.

3. Frequency analysis has been carried out on sub-series both prior and posterior to the change-point (1995) to assess changes in the distribution of annual maximum rainfall series. The frequency analysis using two phases of data should identify recent historical changes in the frequency

and amplitude of rainfall extremes and analyse whether partitioning the rainfall series can improve the fit of distribution function.

Around 39% to 72% of short and long duration rainfall has experienced changes in distributions. As a result of the changes in distributions for annual maximum rainfall series, the estimated quantiles (i.e. 100-year rainfall) derived from the second sub-series are consistently higher compared to full series except for 3-hour to 12-hour rainfall in northwest region, sub-hourly and 12-hour rainfall in the central west region, 6-hour and 1-day rainfall in inland region, and 6-hour to 3-day rainfall in the southwest region.

Furthermore, the amount of data that could not be fitted by any candidate distribution while using full series data has been substantially reduced as discussed in Section 4.4.1.3.

4. Overall, the GEV and L-moments combinations are capable of fitting most of the posterior sub-series (split at the change-point) in most regions for both short and long duration rainfall series based on the calibration and validation data sets. The GEV distribution was able to fit more than half (50%) of the short duration rainfall data and also most of the long duration rainfall series (33% to 80%) especially for the east coast region (80% of the rainfall). However, the performance of LN2 (50% of the data) is better than GEV for long duration rainfall in the inland region.

Three contributions have been generated from this research:

1. Identification of changes in rainfall trend at different locations within Peninsular Malaysia (except for the inland region) as proven by the outcomes from various trend tests namely, the Mann-Kendall trend test; non-stationary tests and; the Sequential Mann-Kendall test.
2. Identification of impacts from climate change on rainfall frequency analysis especially on estimated quantiles. Hence, it is important to take note of the limitations when using full series data (assuming that climate change will have altered the population statistics). Furthermore, it is crucial to detect the trend change-point so that only sub-series data posterior to the change-point are used in analysis.
3. Suggestions on the best combination of probability distribution function and method for parameters estimation for regions within Peninsular Malaysia, incorporating the impacts from climate change.

In short, climate change alters the water resources cycle. The impacts include occurrences of more intense rainfall, spatial and temporal variation in rainfall distribution and hence, water distribution for agricultural, domestic and industrial sectors, etc. By identifying the changes in rainfall trends, this helps in water resources planning and development. More importantly, this thesis highlights the presence of non-stationarity properties of the rainfall series. Hence, the application of more recent data series (posterior to change-point) in frequency analysis is recommended to address the influence of non-stationarity and the effect of climate change. To improve quantiles estimation for each region, it is necessary to identify the best fitted distribution function and parameter estimation method combination for each region due to the spatial variability in rainfall series.

5.2 LIMITATIONS

The first limitation of this study is the length of the record data. As the second part of frequency analysis needs to partition the data series into two sub-series, the length of the recorded data became crucial especially for the accuracy of statistically derived quantiles. Although the accuracy of the present work is limited due to insufficient time coverage of rainfall data, the resulting analyses conducted on shorter time records provides some insight on how subtle changes in the rainfall distribution can be identified. Such situations occur when either (i) the location of the mean has shifted, (ii) the spread has increased/decreased, or (iii) the magnitude or frequency of outliers exhibits some variation thus affecting the skewness and kurtosis of the underlying distribution. Situations involving the latter were the focus of this thesis. It is expected that the method will perform in a more robust manner when provided with more data.

The second limitation of this study is the location of change-point. Although the location of the change-point was determined based on the findings from the Malaysian Meteorological Department (Malaysian Meteorological Department, 2015), the study will be more comprehensive if different locations of change points are tested, or different delineated regions might have different locations of change point.

5.3 RECOMMENDATIONS

In the field of hydrological science, there are always uncertainties about the magnitude of the future changes in hydro-meteorological patterns. However, there appears to be a limited number of research that incorporates the non-stationarity of annual maximum or partial duration rainfall series when conducting frequency analyses. This research has presented the changes in rainfall trend and the need to accommodate non-stationarity in hydrologic statistics.

As the non-stationarity is detected in extreme rainfall, further study should be carried out using the non-stationary model with climatic covariates for the heavy rainfall events is developed. According to the deviance test, the non-stationary model provides a better fit to the data than a classical stationary model (Tramblay et al., 2013). Such model incorporating climatic covariates instead of time allows one to re-evaluate the risk of extreme precipitation on a monthly and seasonal basis, and can also be used with climate model outputs to produce future scenarios.

Also, in view of the impact from climate change, more research is needed to investigate the combined effects of anthropogenic influences and the variability of climate system especially with regard to changes in rainfall trend on streamflow. In this case, as significant increasing trends have been detected across the study area, it is necessary to examine the impact of changes of rainfall trend on water resources and the extent of flood at various urban and rural catchments in Peninsular Malaysia. This will provide some insights into the rainfall-runoff relationship and for the better understanding of its implication on different types of catchments. Further studies also should be conducted to consider other rainfall characteristics such as average rainfall, rain days and other climate change parameters to verify whether a significant trend is present.

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APPENDIX 1: PROBABILITY DENSITY FUNCTION FOR VARIOUS DISTRIBUTION FUNCTIONS

Distribution Functions	Probability Density Function
EV1	$f(x) = \frac{1}{\sigma} \exp\left[-\left(\frac{(\chi-\mu)}{\sigma}\right) \exp\left(-\frac{(\chi-\mu)}{\sigma}\right)\right]$
EV2	$f(x) = \frac{\mu}{\sigma} - \left(\frac{\sigma}{x-\xi}\right)^{\mu+1} exp\left[-\left(\frac{\sigma}{x-\xi}\right)^{\mu}\right], \xi > 0$
EV3	$f(x) = \frac{\xi}{\sigma}\left(\frac{x-\mu}{\sigma}\right)^{(\xi-1)} exp\left[-\left(\frac{x-\mu}{\sigma}\right)^{\xi}\right], \xi > 0$
Inverse EV3	$f(x) = \frac{\xi}{\sigma}\left(\frac{\sigma}{x-\mu}\right)^{(\xi+1)} exp\left[-\left(\frac{\sigma}{x-\mu}\right)^{\xi}\right], \xi < 0$
GEV	$f(x) = \frac{1}{\sigma} exp\left[-\left(1+\xi\frac{(\chi-\mu)}{\sigma}\right)^{-\frac{1}{\xi}}\right]\left(1+\xi\frac{(\chi-\mu)}{\sigma}\right)^{-1-\left(\frac{1}{\xi}\right)}$
TCEV	$f(x) = \left[\frac{\xi_1}{\sigma_1} exp\left(-\frac{x}{\sigma_1}\right) + \frac{\xi_2}{\sigma_2} exp\left(-\frac{\chi}{\sigma_2}\right)\right] exp\left[-\xi_1 exp\left(-\frac{x}{\sigma_1}\right) - \xi_2 exp\left(-\frac{\chi}{\sigma_2}\right)\right]$
LN2	$f(x) = \left[\frac{1}{x\sigma\sqrt{2\pi}}\right] exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right], \sigma > 0$
LN3	$f(x) = \left[\frac{1}{(x-a)\sigma\sqrt{2\pi}}\right] exp\left[-\frac{(\ln((x-a)-\mu)^2}{2\sigma^2}\right]$
P3	$f(x) = \frac{(x-\mu)^{(\xi-1)} exp\left\{-\frac{(x-\mu)}{\sigma}\right\}}{\sigma^{\xi}\Gamma(\xi)}, -\infty \leq \mu < \infty;\ \sigma > 0;\ \xi > 0$
LP3	$f(x) = \left[\frac{(\ln x-\mu)}{\sigma}\right]^{\xi-1}\left\{\frac{exp\left[-\frac{(\ln x-\mu)}{\sigma}\right]}{[\lvert\sigma\rvert\Gamma(\xi)x]}\right\}$
GP2	$f(x) = \frac{1}{\sigma}\left(1-\xi\frac{(\chi)}{\sigma}\right)^{\left(\frac{1}{\xi}\right)-1}$
GP3	$f(x) = \frac{1}{\sigma}\left(1+\xi\frac{(\chi-\mu)}{\sigma}\right)^{-1-\left(\frac{1}{\xi}\right)}$
Wakeby	$x(F) = \mu + \frac{\varepsilon}{\beta}\left[1-(1-F)^{\beta}\right] - \frac{\gamma}{\theta}\left[1-(1-F)^{-\theta}\right]$

Kappa	$f(x) = \frac{1}{\sigma}\left(1 - \frac{k}{\sigma}(x-\mu)\right)^{\frac{1}{\kappa-1}} \left\{1 - h\left[1 - \frac{k}{\sigma}(x-\mu)\right]^{\frac{1}{k}}\right\}^{\frac{1}{h-1}}, \mu > 0;\ \sigma \neq 0$

Where:

F	≡	F(x) is probability density function for Wakeby distribution
f(x)	=	Probability density function for various of distribution functions
h	=	Shape parameter for Kappa distribution
k	=	Shape parameter for Kappa distribution
x	=	Hydrological variable such as rainfall and flood flow data
α	=	Lower boundary value for LN3 distribution
β	=	One of the parameter for Wakeby distribution
γ	=	One of the parameter for Wakeby distribution
ε	=	One of the parameter for Wakeby distribution
θ	=	One of the parameter for Wakeby distribution
μ	=	Location parameter of distribution function
ξ	=	Shape parameter of distribution function
ξ_1, ξ_2	=	Shape parameter for TCEV distribution function
σ	=	Scale parameter of distribution function
σ_1, σ_2	=	Scale parameter for TCEV distribution function

APPENDIX 2: INVERSE DISTRIBUTION FUNCTIONS FOR CANDIDATE DISTRIBUTIONS

Distribution Functions	Inverse Distribution Function
Gumbel (EV1)	$x_T = \mu - \sigma\ ln\left[-\ln\left(1 - {}^{1}/_{T}\right)\right]$
Lognormal (LN2)	$x_T = e^{\mu + u\sigma}$; where: $u = W - \frac{2.515517 + 0.802853W + 0.010328W^2}{1 + 1.432788W + 0.189269W^2 + 0.001308W^3} + \varepsilon(P)$ $W = \sqrt{-2\ln(P)}$ for P<0.5 $\varepsilon(P) < 4.5 \times 10^{-4}$ If P>0.5, then replace P with 1-P and replace restore u in opposite sign.
Generalised Extreme Value (GEV)	$x_T = \mu + \frac{\sigma}{\xi}\left[1 - \left\{-ln\left(1 - \frac{1}{T}\right)\right\}^{\xi}\right]$
Lognormal (LN3)	$x_T = \mathrm{a} + e^{\mu + u\sigma}$; where u is calculated the same way shown in LN2
Log Pearson (LP3)	$x_T = e^{z_T}$; where: $z_T = lnx_T = a + K_T b$ $a = \mu + \sigma\xi$ $b = \sigma\sqrt{\xi}$ $C_s = {}^{2}\!/\!_{\sqrt{\xi}}$ $K_T = \frac{2}{C_s}\left\{\left[\frac{C_s}{6}\left(u - \frac{C_s}{6}\right) + 1\right]^3 - 1\right\}$ u is calculated the same way shown in LN2

APPENDIX 3: DETAILS OF RAINFALL RECORDS

State	Station ID	Stations	Data Available		Record Length		
			From	To	Full series	1st Sub-series	2nd Sub-series
Johor (7)	1437116	Stor JPS Johor Bahru	1971	2011	41	24	17
	1534002	Pusat Kemajuan Per. Pekan Nanas	1979	2011	33	16	17
	1737001	Sek. Men. Bkt. Besar di Kota Tinggi	1975	2011	37	20	17
	1839196	Simpang Mawai-Kuala Sedili	1971	2011	41	24	17
	2025001	Pintu Kawalan Tg. Agas di Muar	1975	2011	37	20	17
	2235163	Ibu Bekalan Kahang di Kluang	1980	2011	32	15	17
	2330009	Ldg. Sg. Labis di Labis	1971	2011	41	24	17
Kedah (5)	5704055	Kedah Peak	1975	2011	37	20	17
	5806066	Jeniang Klinik	1971	2011	41	24	17
	5808001	Bt. 61 Jln. Baling	1982	2011	30	13	17
	6108001	Komplek Rumah Muda	1975	2011	37	20	17
	6206035	Kuala Nerang	1971	2011	41	24	17
Kelantan (2)	4819027	Gua Musang	1972	2011	40	23	17
	5718002	Air Lanas	1981	2011	31	14	17
Kuala Lumpur (6)	3116003	JPS Wilayah Persekutuan	1976	2011	36	19	17
	3116006	Ldg. Edinburgh Site 2	1978	2011	34	17	17
	3216001	Kg. Sg. Tua	1973	2011	39	22	17
	3217001	Ibu Bekalan Km. 16, Gombak	1973	2011	39	22	17
	3217002	Empangan Genting Klang	1973	2011	39	22	17
	3217003	Ibu Bekalan Km. 11, Gombak	1975	2011	37	20	17
Melaka (1)	2224038	Chin Chin (Tepi Jalan)	1971	2011	41	24	17
Negeri Sembilan (2)	2719001	Setor JPS Sikamat Seremban	1971	2011	41	24	17
	2722002	Kg. Sawah Lebar	1971	2011	41	24	17
Pahang (7)	3121143	Simpang Pelangai	1976	2011	36	19	17
	3228174	Sg. Cabang Kanan	1978	2011	34	17	17
	3231163	Kg. Unchang	1974	2011	38	21	17
	3519125	Kuala Marong di Bentong	1973	2011	39	22	17
	3533102	Rumah Pam Pahang Tua di Pekan	1975	2011	37	20	17
	3818054	Stor JPS Raub	1979	2011	33	16	17
	4023001	Kg. Sg. Yap	1974	2011	38	21	17

State	Station ID	Stations	Data Available		Record Length		
			From	To	Full series	1st Sub-series	2nd Sub-series
Perak (8)	4010001	JPS. Telok Intan (Stor)	1971	2011	41	24	17
	4209093	JPS. Telok Sena	1976	2011	36	19	17
	4311001	Pejabat Daerah Kampar	1975	2011	37	20	17
	4409091	Rumah Pam Kubang Haji	1971	2011	41	24	17
	4511111	Politeknik Ungku Omar	1975	2011	37	20	17
	4708084	Ibu Bekalan Talang di Kuala Kangsar	1975	2011	37	20	17
	4811075	Belia Perlop 1, Sg. Siput	1979	2011	33	16	17
	5210069	Stn. Pemeriksaan Hutan Lawin	1971	2011	41	24	17
Perlis (1)	6401002	Padang Katong di Kangar	1975	2011	37	20	17
Pinang (4)	5302001	Taliair Besar Sg. Pinang	1971	2011	41	24	17
	5302003	Kolam Takongan Air Itam	1976	2011	36	19	17
	5402001	Klinik Bkt. Bendera	1976	2011	36	19	17
	5402002	Kolam Bersih Pulau Pinang	1976	2011	36	19	17
Selangor (8)	2917001	RTM Kajang	1976	2011	36	19	17
	3117070	JPS Ampang	1971	2011	41	24	17
	3118102	Sek.Keb.Kg.Sg. Lui	1979	2011	33	16	17
	3411017	Stor JPS Tg.Karang	1971	2011	41	24	17
	3416002	Kg. Kalong Tengah	1979	2011	33	16	17
	3516022	Loji Air Kuala Kubu Bahru	1971	2011	41	24	17
	3613004	Ibu Bekalan Sg. Bernam	1971	2011	41	24	17
	3710006	Rumah Pam JPS Bagan Terap	1971	2011	41	24	17
Terengganu (5)	4734079	Sek. Men. Sultan Omar di Dungun	1971	2011	41	24	17
	4929001	Kg. Embong Sekayu di Ulu Terengganu	1976	2011	36	19	17
	5331048	Setor JPS Kuala Terengganu	1973	2011	39	22	17
	5428001	Kg. Batu Hampar di Chalok Site 1	1978	2011	34	17	17
	5428002	Klinik Chalok Barat Site 2	1978	2011	34	17	17

APPENDIX 4: CORRELATION BETWEEN THE MK TEST AND THE NON-STATIONARY TESTS FOR ANNUAL RAINFALL AND ANNUAL MAXIMUM SERIES

Table 4.A: Correlation between MK test and the non-stationary tests for annual rainfall in northwest region

State	Stations	Annual Total Rainfall		
		MK	Median	MW
Perlis	6401002	-1.373	2.245	1.493
Kedah	5704055	0.632	1.129	0.925
	5806066	0.685	**2.948**	0.979
	5808001	0.464	**3.394**	1.025
	6108001	**1.870**	1.303	**1.890**
	6206035	1.247	1.172	**1.694**
Pinang	5302001	-0.483	0.034	0.370
	5302003	0.913	1.003	0.190
	5402001	-0.395	0.111	0.428
	5402002	0.749	1.003	0.966
Perak	4209093	0.014	0.111	0.903
	4311001	**1.923**	**6.060**	**2.895**
	4409091	**2.145**	1.172	1.601
	4511111	0.981	1.303	0.640
	4708084	**2.603**	**9.745**	**2.834**
	4811075	0.139	0.279	1.081
	5210069	**2.101**	**2.948**	**2.580**

Table 4.B: Correlation between MK test and the non-stationary tests for annual rainfall in central west region

State	Stations	Annual Total Rainfall		
		MK	Median	MW
Perak	4010001	**2.325**	1.172	1.032
Selangor	2917001	1.294	1.003	**1.695**
	3117070	**1.696**	2.406	1.601
	3118102	1.534	0.000	0.324
	3411017	0.865	0.201	1.032
	3416002	**2.433**	2.000	**2.197**
	3516022	1.112	1.172	1.111
	3613004	**2.011**	1.667	1.098
	3710006	1.404	0.201	0.106
Kuala Lumpur	3116003	**2.874**	**5.461**	**2.804**
	3116006	**2.787**	**9.529**	**3.840**
	3216001	0.218	0.033	0.170
	3217001	-0.363	0.033	0.099
	3217002	**2.081**	**13.646**	**3.370**
	3217003	**1.949**	**6.060**	**2.590**
Negeri Sembilan & Melaka	2719001	**4.100**	**12.379**	**3.731**
	2722002	**1.786**	1.172	**2.038**
	2224038	**1.966**	**2.948**	**2.038**

Table 4.C: Correlation between MK test and the non-stationary tests for annual rainfall in southwest region

State	Stations	Annual Total Rainfall		
		MK	Median	MW
Johor	1437116	**2.932**	**2.948**	**1.958**
	1534002	-0.945	0.029	0.684
	1737001	**-1.818**	2.245	**1.737**
	2025001	**-2.315**	2.245	1.585

Table 4.D: Correlation between MK test and the non-stationary tests for annual rainfall in inland region

State	Stations	Annual Total Rainfall		
		MK	Median	MW
Kelantan	4819027	0.663	0.102	0.178
Pahang	3121143	-0.068	1.003	0.808
	3519125	**2.589**	**3.083**	**2.464**
	3818054	0.728	1.500	0.973
	4023001	0.302	0.106	0.367
Johor	2330009	1.382	0.201	1.111

Table 4.E: Correlation between MK test and the non-stationary tests for annual rainfall in east coast region

State	Stations	Annual Total Rainfall		
		MK	Median	MW
Terengganu	4734079	-0.056	2.558	1.059
	4929001	1.294	0.111	0.871
	5331048	0.968	0.033	0.793
	5428001	**2.135**	1.059	1.378
	5428002	**2.283**	1.059	0.947
Pahang	3228174	1.067	0.118	0.809
	3231163	**1.835**	2.661	1.277
	3533102	1.112	0.232	0.975
Johor	1839196	1.089	0.201	0.847
	2235163	-1.281	0.125	0.850
Kelantan	5718002	**1.802**	0.313	0.437

Table 4.F: Correlation between MK test and the non-stationary tests for short duration annual maximum rainfall in northwest region

State	Stations	15-minute				30-minute				1-hour				3-hour			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Perlis	6401002	-0.67	0.70	1.63	GEV-MOM	-0.80	2.25	**1.91**	GEV-MOM	-1.06	2.25	**2.04**	EV1-LM	-1.61	2.25	**1.80**	GEV-LM
Kedah	5704055	**1.90**	**8.19**	**3.06**	GEV-LM	**1.74**	**3.14**	**2.25**	LN3-LM	**1.90**	**6.15**	**1.87**	GEV-MOM	1.38	1.13	1.53	GEV-LM
	5806066	0.96	1.17	0.61	-	-0.08	0.12	0.20	-	-0.17	0.20	0.07	-	-0.57	0.20	0.49	GEV-MOM
	5808001	-0.46	0.14	0.40	LN3-LM	0.68	0.14	0.11	LN2-LM	1.07	**3.39**	0.90	GEV-LM	-0.11	0.14	0.48	GEV-LM
	6108001	-0.14	0.11	1.13	GEV-MOM	0.48	0.81	0.59	EV1-MOM	0.90	0.03	0.09	GEV-MOM	0.96	0.03	0.46	GEV-LM
	6206035	**1.74**	0.20	1.02	GEV-MOM	**2.01**	**2.95**	**1.71**	GEV-LM	**1.72**	1.82	1.30	LN3-LM	0.87	1.17	0.82	GEV-MOM
Pinang	5302001	**1.65**	**2.95**	**2.30**	GEV-MOM	1.45	**2.95**	**2.16**	GEV-MOM	0.44	**2.95**	1.47	GEV-LM	-0.03	0.20	0.57	LN3-LM
	5302003	0.50	0.11	0.38	GEV-MOM	1.19	1.00	0.49	GEV-LM	**2.25**	1.00	0.59	GEV-LM	0.15	1.00	1.17	GEV-LM
	5402001	-0.59	1.00	0.41	-	-0.78	1.00	0.46	-	0.50	1.00	0.02	EV1-MOM	0.18	1.00	0.97	GEV-LM
	5402002	**2.28**	**9.03**	**2.93**	LP3-MLM	**3.31**	**5.46**	**2.96**	GEV-MOM	**2.41**	**5.46**	**2.36**	GEV-MOM	1.54	1.00	0.56	GEV-LM
Perak	4209093	0.45	0.00	0.25	-	**1.81**	**2.79**	0.81	EV1-MOM	1.21	0.11	0.84	EV1-LM	0.53	0.11	0.70	GEV-LM
	4311001	**1.87**	**3.25**	**2.55**	GEV-MOM	**2.26**	**6.06**	**3.00**	GEV-LM	1.58	**6.06**	**3.02**	GEV-MOM	1.24	**9.75**	**2.71**	GEV-MOM
	4409091	**1.70**	**2.95**	1.55	GEV-MOM	**2.48**	1.17	**2.36**	GEV-LM	**2.06**	1.17	1.63	GEV-MOM	**1.92**	1.82	1.31	GEV-LM
	4511111	0.30	0.03	0.35	-	**1.74**	**3.25**	**2.01**	-	**2.37**	**6.06**	**2.47**	-	1.32	1.30	1.45	GEV-MOM
	4708084	-0.14	0.03	0.18	EV1-MOM	0.46	0.03	0.43	GEV-MOM	0.20	0.23	0.15	GEV-LM	0.82	0.23	0.78	GEV-LM
	4811075	0.82	0.28	0.90	GEV-MOM	1.10	1.50	0.87	GEV-MOM	0.85	1.50	0.79	GEV-LM	1.10	**3.69**	1.17	GEV-MOM
	5210069	**1.65**	1.17	**1.75**	GEV-LM	**2.62**	**2.95**	**2.30**	GEV-LM	**1.65**	1.17	**1.73**	GEV-LM	0.53	1.82	1.23	GEV-MOM

Table 4.G: Correlation between MK test and the non-stationary tests for long duration annual maximum rainfall in northwest region

State	Stations	6-hour				12-hour				1-day				3-day			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Perlis	6401002	-1.06	2.25	1.17	LN2-LM	0.01	0.23	0.49	GEV-MOM	0.54	0.23	0.02	GEV-MOM	-0.14	0.03	0.43	LP3-LM
Kedah	5704055	0.24	1.13	0.36	GEV-LM	-0.18	1.13	0.47	LN2-LM	0.02	0.13	0.21	LN3-LM	0.67	1.13	0.64	LN2-LM
	5806066	-0.30	0.92	0.13	GEV-LM	-0.69	2.11	0.74	EV1-MOM	-0.46	2.11	0.56	GEV-LM	-0.15	0.20	0.05	GEV-MOM
	5808001	-0.68	0.00	0.21	EV1-LM	-0.14	0.00	0.63	GEV-MOM	0.46	0.14	0.92	GEV-MOM	0.18	0.14	0.90	GEV-MOM
	6108001	0.88	0.23	0.38	GEV-LM	0.93	0.03	0.46	GEV-LM	1.48	**6.06**	1.52	GEV-LM	**2.21**	**6.06**	**2.23**	GEV-LM
	6206035	1.38	1.17	1.27	GEV-MOM	1.27	1.17	1.09	GEV-LM	**1.99**	0.20	1.22	GEV-LM	**2.51**	**2.95**	**1.96**	LN2-LM
Pinang	5302001	0.03	0.20	0.49	LN2-MLM	-0.89	0.20	0.77	LN2-MLM	-0.82	1.17	0.50	LN2-LM	-0.64	0.03	0.11	LN2-LM
	5302003	-0.42	0.11	1.38	GEV-LM	-0.37	0.11	0.90	GEV-MOM	-0.78	0.11	1.16	GEV-LM	-0.61	1.00	1.22	LN2-MOM
	5402001	-0.56	**2.79**	1.13	GEV-MOM	-1.16	1.00	1.19	EV1-LM	-0.23	0.11	0.27	GEV-MOM	-0.83	1.00	0.08	LP3-MOM(D)
	5402002	1.02	0.00	0.65	LN3-LM	0.80	0.11	0.52	GEV-LM	0.70	0.11	0.70	GEV-LM	0.10	0.11	0.49	LN2-MOM
Perak	4209093	-0.31	0.11	0.03	EV1-LM	-0.45	0.11	0.08	EV1-LM	0.56	0.11	0.40	GEV-LM	-0.18	1.00	0.06	GEV-MOM
	4311001	0.85	**9.75**	**2.97**	EV1-LM	1.09	**14.30**	**3.11**	GEV-MOM	1.37	**9.75**	**3.47**	GEV-MOM	**1.71**	**3.25**	**2.83**	-
	4409091	**1.76**	1.82	1.14	LP3-MLM	**1.90**	1.17	1.20	GEV-LM	0.80	0.67	0.04	LN3-MOM	1.16	0.03	1.16	GEV-LM
	4511111	1.01	1.30	1.07	GEV-LM	0.80	1.30	1.07	GEV-LM	0.01	0.19	0.44	GEV-LM	0.62	1.30	0.70	GEV-MOM
	4708084	0.64	1.30	0.61	EV1-MOM	0.59	1.30	0.50	GEV-LM	0.54	1.30	0.53	LN3-LM	0.09	0.03	0.66	LN3-LM
	4811075	0.30	**3.69**	0.90	EV1-MOM	-0.20	0.28	0.41	GEV-LM	-0.60	0.03	0.07	GEV-MOM	-0.76	1.50	0.11	GEV-LM
	5210069	0.37	1.17	1.46	EV1-LM	0.53	**2.95**	1.58	GEV-LM	0.60	**2.95**	1.48	EV1-MOM	1.52	**8.91**	**2.30**	EV1-MLM

Table 4.H: Correlation between MK test and the non-stationary tests for short duration annual maximum rainfall in central west region

State	Stations	15-minute				30-minute				1-hour				3-hour			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Perak	4010001	**1.79**	1.17	**1.77**	-	1.31	0.20	1.19	-	0.69	0.20	0.32	-	1.52	1.17	1.23	EV1-LM
Selangor	2917001	1.54	1.00	0.68	LN3-LM	**2.14**	**2.79**	**2.14**	GEV-MOM	**2.79**	**2.79**	**2.35**	GEV-MOM	**2.82**	**9.03**	**3.09**	GEV-MOM
	3117070	1.07	1.67	**1.93**	-	0.62	1.17	**1.92**	GEV-LM	0.93	2.41	**2.10**	GEV-MOM	1.16	2.41	1.43	LN2-LM
	3118102	-0.29	0.00	0.32	-	0.42	1.50	0.68	GEV-LM	0.67	0.50	0.87	GEV-MOM	-0.36	0.50	0.18	-
	3411017	0.66	**2.95**	**2.17**	-	0.37	0.42	1.15	EV1-MOM	0.21	0.42	0.56	GEV-LM	-0.42	0.03	0.29	GEV-MOM
	3416002	0.20	0.00	0.50	GEV-LM	0.54	1.50	0.94	GEV-MOM	0.45	1.50	0.72	GEV-MOM	0.11	0.28	0.05	EV1-MOM
	3516022	**2.91**	**17.11**	**3.33**	-	**2.98**	**8.91**	**2.94**	GEV-MOM	1.16	1.17	**1.68**	LP3-MOM (D)	0.17	0.15	0.45	GEV-MOM
	3613004	**2.89**	**5.53**	**2.28**	LN2-MOM	**2.75**	**5.53**	1.54	GEV-MOM	**2.44**	1.17	1.05	GEV-MOM	1.23	1.17	1.05	LN2-LM
	3710006	**1.94**	1.67	1.47	-	**2.33**	1.67	**1.76**	LN3-MOM	0.98	1.17	0.33	LN3-LM	-1.07	0.42	0.34	GEV-MOM
Kuala Lumpur	3116003	1.21	**5.46**	**2.27**	GEV-MOM	**1.84**	**5.46**	**2.17**	LN3-MOM	0.94	0.11	0.98	LN2-LM	1.49	1.00	1.00	GEV-LM
	3116006	1.19	1.89	**1.72**	LN3-MOM	**3.09**	**9.66**	**3.77**	LP3-MOM(D)	**2.70**	**26.47**	**4.67**	LP3-MOM(M)	**2.52**	**9.53**	**3.60**	GEV-LM
	3216001	0.68	1.23	1.30	-	1.50	**3.08**	**2.56**	-	0.07	1.23	1.57	EV1-MOM	-0.29	1.23	1.22	GEV-MOM
	3217001	0.27	0.22	0.74	GEV-MOM	**2.06**	1.23	**1.91**	-	**2.78**	**13.65**	**3.75**	LN3-MOM	1.43	1.23	**1.67**	-
	3217002	1.31	**11.15**	**2.82**	LN2-LM	**3.07**	**13.65**	**4.19**	GEV-MOM	**2.59**	**9.29**	**3.51**	GEV-MOM	0.97	0.01	1.53	EV1-MOM
	3217003	1.19	**6.06**	**2.30**	GEV-LM	**2.76**	**14.30**	**3.66**	GEV-LM	**1.82**	**6.06**	**2.35**	GEV-LM	1.14	1.30	1.43	GEV-MOM
Negeri Sembilan & Melaka	2719001	**2.37**	**5.01**	**2.16**	LN3-LM	**3.16**	**5.53**	**3.33**	GEV-MOM	**2.82**	**17.29**	**3.71**	GEV-LM	**2.80**	**5.01**	**2.92**	GEV-MOM
	2722002	1.41	**6.32**	**3.00**	-	**2.01**	**5.01**	**2.99**	-	**1.97**	**4.50**	**3.03**	-	**2.39**	**5.53**	**3.22**	GEV-MOM
	2224038	-0.75	0.67	0.25	GEV-LM	-0.12	0.67	0.21	GEV-MOM	0.64	0.20	1.03	LP3-MLM	0.37	0.67	0.05	LP3-LM

Table 4.I: Correlation between MK test and the non-stationary tests for long duration annual maximum rainfall in central west region

State	Stations	6-hour				12-hour				1-day				3-day			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Perak	4010001	1.14	1.17	0.97	GEV-MOM	1.25	1.17	0.97	GEV-MOM	0.03	0.03	0.19	GEV-LM	-0.12	0.20	0.33	GEV-LM
Selangor	2917001	**2.47**	**2.79**	**2.61**	GEV-MOM	**1.89**	**2.79**	**2.01**	GEV-MOM	**1.84**	**5.46**	**2.19**	LN2-MLM	1.46	**2.79**	**1.76**	LP3-LM
	3117070	1.54	0.42	**1.68**	LN2-LM	0.46	1.17	1.40	GEV-MOM	0.66	0.42	1.13	EV1-LM	1.05	1.17	1.02	EV1-MLM
	3118102	0.14	0.00	0.13	GEV-MOM	0.11	0.28	0.07	GEV-MOM	0.20	0.50	0.14	GEV-LM	-1.63	2.44	**1.82**	GEV-LM
	3411017	-0.64	1.07	0.45	LN2-LM	-0.84	1.67	0.69	LN3-LM	-0.46	0.03	0.30	LN2-LM	-1.38	2.11	1.15	GEV-LM
	3416002	-0.14	0.03	0.23	GEV-MOM	0.08	0.28	0.61	GEV-LM	0.70	0.03	0.50	GEV-LM	**1.91**	1.50	**2.09**	GEV-LM
	3516022	0.62	0.20	1.02	GEV-MOM	0.46	0.00	0.58	EV1-MOM	0.62	0.20	0.78	LN2-MOM	0.42	**2.95**	1.30	EV1-MLM
	3613004	**1.74**	**5.53**	**1.83**	LN2-LM	1.18	**3.75**	**1.79**	GEV-LM	0.98	1.67	1.32	-	0.82	0.20	0.85	-
	3710006	-1.18	0.03	0.15	LN3-LM	-1.05	0.00	0.15	LN2-LM	**-1.92**	**3.75**	1.52	GEV-LM	-0.91	1.43	0.95	EV1-LM
Kuala Lumpur	3116003	1.27	**2.79**	0.97	GEV-LM	1.05	0.09	0.94	-	**2.03**	**2.79**	**1.97**	-	**2.41**	**9.03**	**2.61**	-
	3116006	**2.34**	**9.53**	**3.67**	LN3-LM	**2.11**	**9.53**	**3.50**	GEV-LM	1.60	**9.53**	**3.07**	GEV-MOM	1.54	**5.77**	**3.46**	GEV-LM
	3216001	-0.85	1.23	0.64	GEV-LM	-1.52	0.69	0.61	GEV-LM	-1.50	0.69	1.29	GEV-MOM	-1.60	0.69	0.98	GEV-LM
	3217001	0.92	0.56	0.81	GEV-MOM	0.36	0.22	0.60	GEV-MOM	0.65	1.23	0.88	GEV-MOM	0.44	0.22	0.61	LN3-MOM
	3217002	0.63	0.22	1.44	-	0.68	1.23	**1.67**	-	0.39	1.23	1.13	-	0.61	**3.08**	1.63	-
	3217003	0.82	0.23	1.22	GEV-LM	0.20	0.23	0.61	LP3-MLM	-0.46	0.03	0.20	GEV-MOM	-0.07	0.70	0.00	EV1-MLM
Negeri Sembilan & Melaka	2719001	**1.79**	1.52	**2.50**	GEV-MOM	0.84	0.92	**1.79**	GEV-MOM	0.08	0.20	0.68	GEV-MOM	**2.15**	**2.95**	**1.85**	GEV-MOM
	2722002	**2.10**	**5.53**	**3.24**	GEV-LM	**2.17**	**5.01**	**2.75**	GEV-LM	**2.06**	0.69	**2.06**	LN2-LM	**1.70**	1.17	1.35	GEV-LM
	2224038	0.69	0.03	0.08	GEV-MOM	**2.10**	1.17	0.90	GEV-MOM	**2.51**	**2.95**	1.42	LN2-LM	**2.12**	0.20	0.99	GEV-LM

Table 4.J: Correlation between MK test and the non-stationary tests for short duration annual maximum rainfall in southwest region

State	Stations	15-minute				30-minute				1-hour				3-hour			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Johor	1437116	-0.98	0.03	0.16	-	-0.35	0.20	0.33	GEV-MOM	0.19	0.20	0.53	GEV-MOM	0.53	0.20	1.11	LN3-LM
	1534002	1.16	1.50	1.33	LN3-LM	**1.69**	**6.86**	1.84	GEV-MOM	**2.46**	**6.86**	2.13	GEV-LM	0.02	1.50	0.94	LN2-LM
	1737001	0.64	0.23	1.33	-	0.80	0.29	0.43	-	-0.09	0.70	0.91	-	0.01	0.70	0.12	-
	2025001	-0.25	0.03	0.08	GEV-LM	-0.46	0.03	0.66	GEV-MOM	-0.46	0.70	0.52	GEV-LM	-0.33	0.03	0.03	LN2-LM

Table 4.K: Correlation between MK test and the non-stationary tests for long duration annual maximum rainfall in southwest region

State	Stations	6-hour				12-hour				1-day				3-day			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Johor	1437116	0.98	**2.95**	1.89	EV1-MLM	1.22	**3.94**	1.76	GEV-LM	1.27	0.03	0.93	-	**3.00**	**5.53**	2.54	GEV-LM
	1534002	-0.45	0.28	0.54	GEV-LM	-1.13	0.03	0.11	GEV-LM	-1.07	0.28	0.00	GEV-LM	-0.11	0.03	0.07	GEV-LM
	1737001	0.17	0.70	0.06	GEV-LM	0.17	0.03	0.24	GEV-LM	-0.14	0.70	0.21	LN3-LM	-0.96	0.70	1.43	EV1-LM
	2025001	-0.33	0.23	0.23	LN2-LM	-0.54	0.03	0.35	EV1-LM	-0.33	0.23	0.05	LN3-LM	-0.51	1.30	0.00	LN2-LM

Table 4.L: Correlation between MK test and the non-stationary tests for short duration annual maximum rainfall in inland region

State	Stations	15-minute				30-minute				1-hour				3-hour			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Kelantan	4819027	0.96	1.17	0.77	GEV-MOM	1.43	1.17	1.10	GEV-LM	-0.06	0.03	0.13	GEV-LM	0.08	0.01	0.09	GEV-MOM
Pahang	3121143	**1.79**	**7.06**	**2.69**	GEV-LM	**2.11**	**2.79**	**2.68**	GEV-MOM	1.57	**2.79**	**2.06**	GEV-MOM	1.46	1.00	1.43	GEV-MOM
	3519125	**2.30**	**12.88**	**3.00**	-	**1.86**	**5.77**	**2.44**	-	0.51	1.23	1.01	-	0.97	1.95	**1.69**	-
	3818054	**1.69**	**3.69**	1.44	GEV-LM	**1.81**	1.50	1.12	LN3-MOM	0.20	0.03	0.41	GEV-MOM	-1.04	2.44	1.21	EV1-MOM
	4023001	0.45	2.66	0.78	-	0.65	0.96	0.73	EV1-MLM	0.08	0.11	0.07	GEV-MOM	-0.20	0.47	0.82	EV1-MLM
Johor	2330009	1.18	1.17	1.01	-	1.49	0.20	1.16	-	0.75	0.03	0.32	EV1-MLM	0.78	0.03	0.58	GEV-LM

Table 4.M: Correlation between MK test and the non-stationary tests for long duration annual maximum rainfall in inland region

State	Stations	6-hour				12-hour				1-day				3-day			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Kelantan	4819027	0.66	0.20	0.53	LN2-LM	0.62	0.20	0.21	GEV-LM	0.21	0.20	0.28	EV1-MOM	-0.87	0.01	0.66	GEV-LM
Pahang	3121143	1.16	0.11	1.14	GEV-MOM	1.05	1.00	1.16	GEV-MOM	0.48	0.11	0.44	EV1-MLM	-0.01	1.00	0.70	GEV-MOM
	3519125	0.44	0.01	1.32	-	0.39	0.22	1.32	-	1.31	**5.77**	**1.83**	-	1.16	1.23	1.42	-
	3818054	0.08	0.03	0.23	GEV-LM	1.07	**3.69**	0.67	EV1-LM	0.79	0.28	0.41	GEV-LM	-1.04	0.03	0.23	LN2-LM
	4023001	-0.45	0.96	1.00	GEV-MOM	-0.81	0.96	1.38	-	-0.68	0.11	1.22	GEV-MOM	**-1.79**	2.66	**2.22**	-
Johor	2330009	0.89	0.20	1.11	LN2-LM	0.84	0.20	1.19	LN2-LM	0.82	0.20	1.03	LN2-LM	0.48	0.03	0.56	GEV-LM

Table 4.N: Correlation between MK test and the non-stationary tests for short duration annual maximum rainfall in east coast region

State	Stations	15-minute				30-minute				1-hour				3-hour			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Terengganu	4734079	0.10	0.92	0.82	-	-0.33	0.03	0.33	-	0.19	0.20	0.29	-	-0.17	1.17	0.17	-
	4929001	1.46	**2.79**	**1.90**	-	1.32	1.00	1.62	-	0.97	0.11	0.97	-	**1.65**	0.11	1.32	EV1-LM
	5331048	0.41	1.23	0.77	GEV-MOM	0.90	0.22	0.82	GEV-LM	0.24	1.23	0.54	GEV-MOM	-0.29	0.22	0.11	GEV-LM
	5428001	0.15	0.12	0.71	LN3-LM	**1.87**	1.06	**2.00**	LP3-MLM	**1.72**	**2.94**	**2.05**	GEV-LM	0.80	1.89	1.26	GEV-LM
	5428002	1.04	1.06	1.29	LN3-LM	0.89	0.12	1.12	LN2-LM	0.95	0.12	0.81	GEV-LM	**1.96**	**5.77**	**1.98**	GEV-LM
Pahang	3228174	**2.31**	**2.94**	**2.74**	-	**2.34**	**2.94**	**2.03**	-	1.45	1.06	1.33	-	-0.42	0.12	0.05	-
	3231163	1.03	0.96	1.38	GEV-LM	1.36	0.38	1.22	GEV-MOM	**1.66**	0.96	1.28	GEV-LM	**2.72**	**5.22**	**2.16**	EV1-LM
	3533102	**2.34**	**14.30**	**3.37**	-	1.64	**6.06**	**1.98**	EV1-MLM	1.58	**6.06**	**2.01**	LN2-LM	1.11	1.30	1.25	LN2-MLM
Johor	1839196	1.27	0.20	0.89	GEV-LM	**2.98**	**8.91**	**2.69**	EV1-MOM	1.58	1.17	1.20	LN3-LM	0.42	0.03	0.07	GEV-MOM
	2235163	0.44	0.13	0.55	EV1-MOM	**1.93**	**3.14**	**1.79**	GEV-LM	0.60	0.13	0.59	GEV-MOM	0.63	0.54	0.38	GEV-LM
Kelantan	5718002	1.44	**6.15**	**2.51**	-	**2.42**	**6.15**	**3.19**	-	**3.03**	**10.17**	**3.19**	-	**2.06**	1.13	**1.74**	-

Table 4.O: Correlation between MK test and the non-stationary tests for long duration annual maximum rainfall in east coast region

State	Stations	6-hour				12-hour				1-day				3-day			
		MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF	MK	Median	MW	PDF
Terengganu	4734079	0.46	0.20	0.42	-	1.02	0.03	0.77	-	1.16	1.17	0.95	-	0.55	0.03	0.15	GEV-LM
	4929001	**1.98**	1.00	1.54	LN3-LM	**2.06**	**2.79**	**1.98**	EV1-LM	1.19	1.00	1.16	LN2-LM	1.24	**2.79**	1.09	LN2-LM
	5331048	-0.65	0.03	0.13	GEV-LM	-1.09	0.03	0.77	LN2-MOM	-1.45	0.69	0.82	LN2-LM	-1.40	0.03	0.65	LP3-LM
	5428001	0.53	0.12	0.81	EV1-LM	-0.18	0.12	0.12	GEV-MOM	-0.56	0.12	0.36	LN2-MOM	-0.83	0.12	0.71	LN2-MOM
	5428002	**1.90**	1.06	1.46	EV1-LM	1.39	1.06	1.36	-	0.65	1.06	0.50	GEV-MOM	0.21	0.12	0.26	LN2-MOM
Pahang	3228174	0.80	1.06	0.90	-	0.95	0.12	1.02	-	0.00	0.12	0.12	-	-0.09	1.06	0.31	-
	3231163	**3.07**	2.66	**2.31**	LN2-LM	**2.14**	0.96	1.25	LN2-LM	0.98	0.11	0.10	GEV-LM	0.75	0.11	0.26	LN2-MOM
	3533102	0.72	0.23	0.64	LP3-LM	0.25	0.23	0.03	LN2-LM	0.54	0.23	0.31	LN3-LM	1.40	0.23	0.64	LN3-LM
Johor	1839196	0.30	0.67	0.12	GEV-LM	0.60	0.67	0.24	GEV-LM	0.75	0.20	0.60	LN3-LM	0.73	0.20	0.45	LN2-MLM
	2235163	-0.57	0.13	0.36	-	-1.09	0.13	1.02	-	-0.70	1.13	0.59	-	**-1.70**	1.13	1.51	GEV-MOM
Kelantan	5718002	0.66	0.13	0.93	-	0.92	0.13	0.89	GEV-LM	0.44	1.13	0.17	LP3-LM	0.28	0.13	0.02	GEV-LM

APPENDIX 5: BEST FITTED DISTRIBUTION FUNCTIONS FOR FULL SERIES DATA AND BOTH SUB-SERIES DATA

Table 5.A: Hydrologic frequency analysis results for 15-minute and 30-minute rainfall series in northwest region

State	Stations	15-minute			30-minute		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perlis	6401002	GEV-MOM	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-MOM
Kedah	5704055	GEV-LM	GEV-MOM	GEV-LM	LN3-LM	GEV-LM	GEV-LM
	5806066	-	-	GEV-MOM	-	-	LN2-LM
	5808001	LN3-LM	GEV-LM	LN2-MOM	LN2-LM	GEV-LM	LN2-MLM
	6108001	GEV-MOM	GEV-MOM	GEV-MOM	EV1-MOM	LN2-MOM	GEV-MOM
	6206035	GEV-MOM	GEV-MOM	GEV-MOM	GEV-LM	GEV-LM	GEV-MOM
Pinang	5302001	GEV-MOM	EV1-LM	EV1-MOM	GEV-MOM	LN2-LM	GEV-LM
	5302003	GEV-MOM	EV1-LM	LN3-LM	GEV-LM	GEV-LM	GEV-LM
	5402001	-	GEV-LM	-	-	GEV-MOM	-
	5402002	LP3-MLM	GEV-LM	GEV-LM	GEV-MOM	LN2-LM	LN2-MOM
Perak	4209093	-	-	GEV-MOM	EV1-MOM	EV1-LM	EV1-LM
	4311001	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	EV1-MOM
	4409091	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-MOM
	4511111	-	GEV-MOM	-	-	GEV-LM	-
	4708084	EV1-MOM	LN2-LM	LN2-MLM	GEV-MOM	GEV-LM	GEV-LM
	4811075	GEV-MOM	GEV-MOM	EV1-MLM	GEV-MOM	GEV-MOM	LN2-LM
	5210069	GEV-LM	GEV-LM	GEV-LM	GEV-LM	LN3-LM	EV1-MLM

Table 5.B: Hydrologic frequency analysis results for one-hour and three-hour rainfall series in northwest region

State	Stations	1-hour			3-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perlis	6401002	EV1-LM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM
Kedah	5704055	GEV-MOM	LN2-LM	GEV-LM	GEV-LM	-	GEV-MOM
	5806066	-	-	GEV-LM	GEV-MOM	GEV-LM	GEV-MOM
	5808001	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-MOM
	6108001	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	LN2-MOM	GEV-LM
	6206035	LN3-LM	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM
Pinang	5302001	GEV-LM	GEV-LM	GEV-LM	LN3-LM	LN2-LM	LN2-LM
	5302003	GEV-LM	LN2-LM	GEV-LM	GEV-LM	GEV-LM	GEV-MOM
	5402001	EV1-MOM	GEV-LM	LN2-LM	GEV-LM	GEV-LM	GEV-LM
	5402002	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	-	GEV-LM
Perak	4209093	EV1-LM	LN2-LM	LN2-MOM	GEV-LM	GEV-MOM	LN2-LM
	4311001	GEV-MOM	GEV-LM	GEV-MOM	GEV-MOM	GEV-LM	-
	4409091	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	GEV-MOM	LN2-LM
	4511111	-	GEV-MOM	-	GEV-MOM	LP3-LM	-
	4708084	GEV-LM	EV1-MLM	LN2-LM	GEV-LM	GEV-LM	GEV-LM
	4811075	GEV-LM	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	LN2-MLM
	5210069	GEV-LM	GEV-LM	EV1-MLM	GEV-MOM	GEV-LM	LN3-LM

Table 5.C: Hydrologic frequency analysis results for six-hour and 12-hour rainfall series in northwest region

State	Stations	6-hour			12-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perlis	6401002	LN2-LM	LN2-MOM	GEV-LM	GEV-MOM	GEV-MOM	LN2-MOM
Kedah	5704055	GEV-LM	GEV-LM	LN2-MOM	LN2-LM	EV1-MLM	LN2-LM
	5806066	GEV-LM	GEV-LM	GEV-LM	EV1-MOM	GEV-LM	GEV-LM
	5808001	EV1-LM	GEV-MOM	GEV-MOM	GEV-MOM	GEV-LM	GEV-LM
	6108001	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	LN2-MOM	GEV-LM
	6206035	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-MOM
Pinang	5302001	LN2-MLM	GEV-MOM	GEV-LM	LN2-MLM	EV1-MLM	-
	5302003	GEV-LM	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	GEV-MOM
	5402001	GEV-MOM	GEV-MOM	LN2-LM	EV1-LM	LN2-LM	GEV-LM
	5402002	LN3-LM	LN2-LM	EV1-MLM	GEV-LM	LN2-MOM	GEV-LM
Perak	4209093	EV1-LM	GEV-MOM	GEV-MOM	EV1-LM	LN2-LM	GEV-MOM
	4311001	EV1-LM	GEV-MOM	LN2-MOM	GEV-MOM	GEV-MOM	GEV-LM
	4409091	LP3-MLM	GEV-LM	LN2-MLM	GEV-LM	GEV-LM	GEV-MOM
	4511111	GEV-LM	GEV-LM	EV1-MOM	GEV-LM	GEV-LM	EV1-MLM
	4708084	EV1-MOM	GEV-LM	LN2-LM	GEV-LM	GEV-LM	LN2-LM
	4811075	EV1-MOM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	EV1-LM
	5210069	EV1-LM	EV1-LM	GEV-LM	GEV-LM	EV1-LM	GEV-LM

Table 5.D: Hydrologic frequency analysis results for one-day and three-day rainfall series in northwest region

State	Stations	1-day			3-day		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perlis	6401002	GEV-MOM	GEV-MOM	LN3-LM	LP3-LM	LN2-LM	GEV-MOM
Kedah	5704055	LN3-LM	GEV-LM	GEV-LM	LN2-LM	LN3-LM	LN2-LM
	5806066	GEV-LM	EV1-MOM	EV1-MLM	GEV-MOM	GEV-LM	LN2-LM
	5808001	GEV-MOM	GEV-LM	LN2-LM	GEV-MOM	GEV-LM	GEV-MOM
	6108001	GEV-LM	EV1-LM	GEV-MOM	GEV-LM	EV1-MLM	GEV-LM
	6206035	GEV-LM	GEV-LM	GEV-MOM	LN2-LM	EV1-LM	GEV-LM
Pinang	5302001	LN2-LM	LN2-LM	-	LN2-LM	LN2-LM	EV1-MLM
	5302003	GEV-LM	GEV-LM	LN2-LM	LN2-MOM	LN2-LM	LN2-LM
	5402001	GEV-MOM	LN2-LM	EV1-MLM	LP3-MOM(D)	EV1-MOM	LN2-LM
	5402002	GEV-LM	GEV-LM	GEV-LM	LN2-MOM	LN2-LM	GEV-LM
Perak	4209093	GEV-LM	LN2-MOM	GEV-LM	GEV-MOM	GEV-LM	LN3-LM
	4311001	GEV-MOM	LP3-MOM(D)	GEV-MOM	-	GEV-LM	GEV-LM
	4409091	LN3-MOM	LN3-LM	GEV-LM	GEV-LM	GEV-MOM	GEV-MOM
	4511111	GEV-LM	GEV-LM	GEV-MOM	GEV-MOM	LN2-LM	LN2-MLM
	4708084	LN3-LM	EV1-MOM	EV1-MOM	LN3-LM	GEV-MOM	GEV-MOM
	4811075	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	-
	5210069	EV1-MOM	LN2-MLM	GEV-LM	EV1-MLM	GEV-MOM	EV1-LM

Table 5.E: Hydrologic frequency analysis results for 15-minute and 30-minute rainfall series in central west region

State	Stations	15-minute			30-minute		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perak	4010001	-	GEV-LM	-	-	-	-
Selangor	2917001	LN3-LM	GEV-LM	GEV-LM	GEV-MOM	GEV-MOM	EV1-LM
	3117070	-	GEV-LM	GEV-LM	GEV-LM	-	GEV-LM
	3118102	-	GEV-LM	GEV-LM	GEV-LM	GEV-LM	LN2-LM
	3411017	-	GEV-MOM	GEV-LM	EV1-MOM	GEV-MOM	GEV-LM
	3416002	GEV-LM	LN3-LM	GEV-MOM	GEV-MOM	GEV-LM	GEV-MOM
	3516022	-	-	GEV-MOM	GEV-MOM	GEV-LM	GEV-MOM
	3613004	LN2-MOM	EV1-MOM	GEV-LM	GEV-MOM	GEV-MOM	GEV-LM
	3710006	-	LN2-MOM	GEV-LM	LN3-MOM	-	GEV-LM
Kuala Lumpur	3116003	GEV-MOM	GEV-LM	GEV-LM	LN3-MOM	GEV-LM	GEV-MOM
	3116006	LN3-MOM	GEV-LM	GEV-LM	LP3-MOM(D)	GEV-MOM	LN2-LM
	3216001	-	GEV-MOM	-	-	GEV-MOM	-
	3217001	GEV-MOM	GEV-LM	GEV-MOM	-	GEV-MOM	GEV-MOM
	3217002	LN2-LM	LN2-LM	-	GEV-MOM	-	EV1-MLM
	3217003	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	-	LN2-MOM
Negeri Sembilan & Melaka	2719001	LN3-LM	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM
	2722002	-	GEV-LM	-	-	GEV-LM	-
	2224038	GEV-LM	LN2-LM	GEV-LM	GEV-MOM	GEV-LM	EV1-MLM

Table 5.F: Hydrologic frequency analysis results for one-hour and three-hour rainfall series in central west region

State	Stations	1-hour			3-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perak	4010001	-	-	GEV-LM	EV1-LM	LN2-LM	GEV-MOM
Selangor	2917001	GEV-MOM	GEV-LM	LN2-LM	GEV-MOM	LN3-MOM	GEV-LM
	3117070	GEV-MOM	GEV-MOM	GEV-MOM	LN2-LM	GEV-LM	GEV-LM
	3118102	GEV-MOM	GEV-LM	GEV-LM	-	GEV-LM	GEV-LM
	3411017	GEV-LM	GEV-LM	GEV-LM	GEV-MOM	EV1-MLM	LN2-LM
	3416002	GEV-MOM	GEV-LM	GEV-MOM	EV1-MOM	EV1-MLM	EV1-MLM
	3516022	LP3-MOM (D)	GEV-LM	GEV-MOM	GEV-MOM	GEV-MOM	GEV-MOM
	3613004	GEV-MOM	GEV-LM	GEV-LM	LN2-LM	GEV-LM	GEV-LM
	3710006	LN3-LM	GEV-MOM	LN2-LM	GEV-MOM	GEV-MOM	GEV-LM
Kuala Lumpur	3116003	LN2-LM	GEV-LM	LN2-MLM	GEV-LM	GEV-LM	GEV-MOM
	3116006	LP3-MOM(M)	GEV-LM	GEV-MOM	GEV-LM	LN3-LM	GEV-LM
	3216001	EV1-MOM	GEV-MOM	GEV-LM	GEV-MOM	GEV-MOM	GEV-LM
	3217001	LN3-MOM	-	EV1-MLM	-	LP3-MLM	EV1-MLM
	3217002	GEV-MOM	GEV-LM	GEV-MOM	EV1-MOM	GEV-LM	GEV-LM
	3217003	GEV-LM	GEV-LM	LN2-MLM	GEV-MOM	GEV-MOM	GEV-MOM
Negeri Sembilan & Melaka	2719001	GEV-LM	GEV-MOM	EV1-MLM	GEV-MOM	EV1-MOM	LN2-LM
	2722002	-	GEV-MOM	-	GEV-MOM	GEV-MOM	GEV-MOM
	2224038	LP3-MLM	GEV-MOM	GEV-LM	LP3-LM	GEV-MOM	LN2-LM

Table 5.G: Hydrologic frequency analysis results for six-hour and 12-hour rainfall series in central west region

State	Stations	6-hour			12-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perak	4010001	GEV-MOM	EV1-LM	GEV-LM	GEV-MOM	GEV-MOM	EV1-MOM
Selangor	2917001	GEV-MOM	GEV-LM	GEV-LM	GEV-MOM	EV1-LM	GEV-LM
	3117070	LN2-LM	GEV-LM	LN2-LM	GEV-MOM	GEV-MOM	GEV-MOM
	3118102	GEV-MOM	GEV-LM	LN2-MOM	GEV-MOM	GEV-LM	GEV-MOM
	3411017	LN2-LM	GEV-LM	LN2-MOM	LN3-LM	GEV-LM	LN2-MOM
	3416002	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	LN2-LM
	3516022	GEV-MOM	GEV-LM	GEV-MOM	EV1-MOM	LP3-MOM(M)	GEV-MOM
	3613004	LN2-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM
	3710006	LN3-LM	GEV-MOM	GEV-LM	LN2-LM	LN2-LM	GEV-LM
Kuala Lumpur	3116003	GEV-LM	EV1-LM	GEV-LM	-	LN2-LM	-
	3116006	LN3-LM	LP3-LM	GEV-LM	GEV-LM	LN3-LM	GEV-LM
	3216001	GEV-LM	GEV-LM	GEV-LM	GEV-LM	LN2-LM	GEV-MOM
	3217001	GEV-MOM	GEV-MOM	EV1-MLM	GEV-MOM	GEV-MOM	EV1-LM
	3217002	-	GEV-LM	GEV-MOM	-	-	GEV-MOM
	3217003	GEV-LM	GEV-LM	GEV-MOM	LP3-MLM	EV1-MLM	LN2-LM
Negeri Sembilan & Melaka	2719001	GEV-MOM	GEV-MOM	EV1-LM	GEV-MOM	LN2-MOM	LN2-LM
	2722002	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM
	2224038	GEV-MOM	GEV-LM	LN2-LM	LN3-LM	GEV-LM	GEV-LM

Table 5.H: Hydrologic frequency analysis results for one-day and three-day rainfall series in central west region

State	Stations	1-day			3-day		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Perak	4010001	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM
Selangor	2917001	LN2-MLM	-	EV1-MLM	LP3-LM	GEV-MOM	EV1-MOM
	3117070	EV1-LM	GEV-MOM	LN2-MLM	EV1-MLM	GEV-MOM	LN2-LM
	3118102	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	EV1-LM
	3411017	LN2-LM	LN2-LM	LN2-LM	GEV-LM	GEV-LM	GEV-LM
	3416002	GEV-LM	GEV-LM	LN2-LM	GEV-LM	GEV-LM	LN2-LM
	3516022	LN2-MOM	GEV-LM	GEV-LM	EV1-MLM	GEV-LM	LN2-MLM
	3613004	-	GEV-LM	-	-	GEV-MOM	-
	3710006	GEV-LM	GEV-LM	EV1-MLM	EV1-LM	LN2-MOM	GEV-MOM
Kuala Lumpur	3116003	-	GEV-LM	-	-	GEV-LM	-
	3116006	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM
	3216001	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM
	3217001	GEV-MOM	GEV-MOM	GEV-MOM	LN3-MOM	LN3-LM	EV1-MLM
	3217002	-	GEV-LM	LN2-MLM	-	GEV-LM	GEV-LM
	3217003	GEV-MOM	GEV-LM	GEV-LM	EV1-MLM	LN2-LM	GEV-LM
Negeri Sembilan & Melaka	2719001	GEV-MOM	GEV-MOM	LN2-LM	GEV-MOM	LN2-LM	GEV-MOM
	2722002	LN2-LM	LN2-MOM	GEV-LM	GEV-LM	LN2-LM	LN3-LM
	2224038	LN2-LM	LN2-LM	LN2-LM	GEV-LM	GEV-LM	GEV-LM

Table 5.I: Hydrologic frequency analysis results for 15-minute and 30-minute rainfall series in southwest region

State	Stations	15-minute			30-minute		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Johor	1437116	-	GEV-MOM	GEV-LM	GEV-MOM	GEV-MOM	GEV-MOM
	1534002	LN3-LM	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	GEV-MOM
	1737001	-	-	LN2-LM	-	-	LN2-LM
	2025001	GEV-LM	GEV-LM	GEV-LM	GEV-MOM	EV1-LM	-

Table 5.J: Hydrologic frequency analysis results for one-hour and three-hour rainfall series in southwest region

State	Stations	1-hour			3-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Johor	1437116	GEV-MOM	GEV-MOM	GEV-LM	LN3-LM	GEV-MOM	EV1-LM
	1534002	GEV-LM	GEV-LM	GEV-LM	LN2-LM	GEV-LM	EV1-LM
	1737001	-	-	GEV-LM	-	-	LN2-LM
	2025001	GEV-LM	LN2-LM	GEV-LM	LN2-LM	GEV-MOM	GEV-LM

Table 5.K: Hydrologic frequency analysis results for six-hour and 12-hour rainfall series in southwest region

State	Stations	6-hour			12-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Johor	1437116	EV1-MLM	GEV-MOM	LN2-MOM	GEV-LM	GEV-LM	GEV-MOM
	1534002	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	GEV-MOM
	1737001	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	LN3-LM
	2025001	LN2-LM	GEV-LM	EV1-MLM	EV1-LM	GEV-LM	GEV-LM

Table 5.L: Hydrologic frequency analysis results for one-day and three-day rainfall series in southwest region

State	Stations	1-day			3-day		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Johor	1437116	-	GEV-LM	-	GEV-LM	GEV-LM	GEV-LM
	1534002	GEV-LM	GEV-LM	LN2-LM	GEV-LM	GEV-LM	EV1-MLM
	1737001	LN3-LM	GEV-LM	LN2-LM	EV1-LM	LN2-MOM	GEV-LM
	2025001	LN3-LM	LN2-LM	LN2-LM	LN2-LM	GEV-LM	GEV-LM

Table 5.M: Hydrologic frequency analysis results for 15-minute and 30-minute rainfall series in inland region

State	Stations	15-minute			30-minute		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Kelantan	4819027	GEV-MOM	GEV-MOM	GEV-LM	GEV-LM	LN2-MOM	GEV-MOM
Pahang	3121143	GEV-LM	GEV-MOM	GEV-LM	GEV-MOM	LN3-LM	GEV-LM
	3519125	-	-	-	-	-	-
	3818054	GEV-LM	LN2-LM	GEV-MOM	LN3-MOM	LN2-LM	-
	4023001	-	EV1-MLM	GEV-MOM	EV1-MLM	GEV-MOM	-
Johor	2330009	-	LN3-LM	GEV-LM	-	GEV-LM	GEV-LM

Table 5.N: Hydrologic frequency analysis results for one-hour and three-hour rainfall series in inland region

State	Stations	1-hour			3-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Kelantan	4819027	GEV-LM	GEV-MOM	LN3-LM	GEV-MOM	GEV-LM	GEV-LM
Pahang	3121143	GEV-MOM	GEV-MOM	EV1-MOM	GEV-MOM	GEV-MOM	EV1-MOM
	3519125	-	GEV-LM	-	-	GEV-LM	-
	3818054	GEV-MOM	GEV-MOM	GEV-MOM	EV1-MOM	GEV-MOM	EV1-LM
	4023001	GEV-MOM	EV1-LM	GEV-MOM	EV1-MLM	LN2-LM	GEV-MOM
Johor	2330009	EV1-MLM	GEV-MOM	GEV-LM	GEV-LM	GEV-MOM	LN2-LM

Table 5.O: Hydrologic frequency analysis results for six-hour and 12-hour rainfall series in inland region

State	Stations	6-hour			12-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Kelantan	4819027	LN2-LM	LN2-MOM	GEV-LM	GEV-LM	GEV-MOM	GEV-MOM
Pahang	3121143	GEV-MOM	GEV-LM	EV1-LM	GEV-MOM	GEV-LM	GEV-LM
	3519125	-	GEV-LM	-	-	LN2-LM	-
	3818054	GEV-LM	GEV-LM	LN2-LM	EV1-LM	GEV-MOM	GEV-LM
	4023001	GEV-MOM	GEV-LM	GEV-MOM	-	GEV-LM	-
Johor	2330009	LN2-LM	GEV-LM	LP3-LM	LN2-LM	LN2-LM	LN2-LM

Table 5.P: Hydrologic frequency analysis results for one-day and three-day rainfall series in inland region

State	Stations	1 day			3 days		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Kelantan	4819027	EV1-MOM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	GEV-LM
Pahang	3121143	EV1-MLM	GEV-MOM	GEV-MOM	GEV-MOM	GEV-MOM	LN2-LM
	3519125	-	GEV-LM	-	-	GEV-MOM	-
	3818054	GEV-LM	GEV-MOM	LN2-LM	LN2-LM	EV1-MOM	GEV-LM
	4023001	GEV-MOM	GEV-LM	GEV-MOM	-	-	GEV-MOM
Johor	2330009	LN2-LM	GEV-LM	LN2-LM	GEV-LM	GEV-LM	GEV-LM

Table 5.Q: Hydrologic frequency analysis results for 15-minute and 30-minute rainfall series in east coast region

State	Stations	15-minute			30-minute		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Terengganu	4734079	-	LN3-MOM	-	-	-	-
	4929001	-	EV1-LM	-	-	GEV-LM	-
	5331048	GEV-MOM	EV1-MLM	GEV-LM	GEV-LM	GEV-LM	GEV-LM
	5428001	LN3-LM	LP3-MOM(M)	LN3-LM	LP3-MLM	LP3-MOM(M)	GEV-LM
	5428002	LN3-LM	GEV-LM	GEV-LM	LN2-LM	LP3-LM	GEV-LM
Pahang	3228174	-	GEV-MOM	-	-	GEV-LM	-
	3231163	GEV-LM	LN2-LM	LN2-LM	GEV-MOM	GEV-MOM	GEV-LM
	3533102	-	GEV-LM	-	EV1-MLM	GEV-LM	LP3-LM
Johor	1839196	GEV-LM	GEV-LM	GEV-LM	EV1-MOM	GEV-LM	GEV-MOM
	2235163	EV1-MOM	GEV-LM	GEV-LM	GEV-LM	GEV-LM	GEV-LM
Kelantan	5718002	-	GEV-LM	-	-	GEV-LM	-

Table 5.R: Hydrologic frequency analysis results for one-hour and three-hour rainfall series in east coast region

State	Stations	1-hour			3-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Terengganu	4734079	-	GEV-LM	-	-	GEV-LM	-
	4929001	-	GEV-LM	-	EV1-LM	GEV-MOM	LN2-MOM
	5331048	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM
	5428001	GEV-LM	LN2-LM	EV1-MOM	GEV-LM	LN2-LM	GEV-LM
	5428002	GEV-LM	GEV-LM	LN2-LM	GEV-LM	GEV-MOM	GEV-LM
Pahang	3228174	-	GEV-LM	-	-	GEV-MOM	-
	3231163	GEV-LM	GEV-LM	LN2-LM	EV1-LM	GEV-LM	EV1-MOM
	3533102	LN2-LM	GEV-LM	LP3-MOM(D)	LN2-MLM	LN2-MOM	LN2-LM
Johor	1839196	LN3-LM	GEV-LM	GEV-LM	GEV-MOM	GEV-LM	GEV-LM
	2235163	GEV-MOM	GEV-MOM	GEV-MOM	GEV-LM	GEV-MOM	GEV-LM
Kelantan	5718002	-	EV1-MOM	-	-	GEV-MOM	-

Table 5.S: Hydrologic frequency analysis results for six-hour and 12-hour rainfall series in east coast region

State	Stations	6-hour			12-hour		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Terengganu	4734079	-	GEV-LM	-	-	GEV-LM	-
	4929001	LN3-LM	GEV-MOM	LP3-MOM (M)	EV1-LM	GEV-LM	LP3-MLM
	5331048	GEV-LM	GEV-LM	GEV-LM	LN2-MOM	LN2-LM	GEV-LM
	5428001	EV1-LM	LN2-MOM	EV1-LM	GEV-MOM	LN2-LM	GEV-LM
	5428002	EV1-LM	GEV-LM	GEV-MOM	-	LN2-LM	GEV-LM
Pahang	3228174	-	GEV-MOM	-	-	GEV-LM	-
	3231163	LN2-LM	LN3-LM	LN2-LM	LN2-LM	LN2-LM	GEV-LM
	3533102	LP3-LM	GEV-LM	LN2-LM	LN2-LM	LN2-LM	LN3-LM
Johor	1839196	GEV-LM	EV1-LM	GEV-MOM	GEV-LM	LP3-MOM(M)	-
	2235163	-	-	GEV-LM	-	GEV-LM	GEV-LM
Kelantan	5718002	-	EV1-MOM	-	GEV-LM	LN2-LM	GEV-LM

Table 5.T: Hydrologic frequency analysis results for one-day and three-day rainfall series in east coast region

State	Stations	1 day			3 days		
		Full Series	1st series	2nd series	Full Series	1st series	2nd series
Terengganu	4734079	-	GEV-LM	-	GEV-LM	GEV-LM	-
	4929001	LN2-LM	GEV-LM	LP3-MLM	LN2-LM	LN2-LM	GEV-LM
	5331048	LN2-LM	LN2-LM	GEV-LM	LP3-LM	GEV-MOM	GEV-LM
	5428001	LN2-MOM	EV1-LM	GEV-LM	LN2-MOM	LN2-MOM	GEV-LM
	5428002	GEV-MOM	GEV-MOM	GEV-LM	LN2-MOM	GEV-LM	GEV-LM
Pahang	3228174	-	GEV-MOM	-	-	GEV-LM	-
	3231163	GEV-LM	GEV-LM	GEV-LM	LN2-MOM	LP3-LM	GEV-LM
	3533102	LN3-LM	GEV-LM	GEV-LM	LN3-LM	GEV-LM	GEV-LM
Johor	1839196	LN3-LM	LP3-MOM(D)	GEV-LM	LN2-MLM	LN2-MLM	LP3-LM
	2235163	-	GEV-MOM	GEV-MOM	GEV-MOM	LN2-MOM	GEV-LM
Kelantan	5718002	LP3-LM	GEV-MOM	GEV-LM	GEV-LM	GEV-LM	EV1-LM

APPENDIX 6: 100-YEAR DESIGN STORM FROM DURATIONS OF 15-MINUTE TO 72-HOUR FOR EACH DELINEATED REGION

Table 6.A: 100-year design storm from durations of 15-minute (unit in mm)

Regions	State	Stations	15-minute		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	51.87	43.08	**-16.95**
	Kedah	5704055	48.48	54.17	**11.73**
		5806066	-	45.18	-
		5808001	49.55	42.12	**-15.00**
		6108001	64.35	68.94	**7.14**
		6206035	51.57	50.25	-2.56
	Pinang	5302001	54.88	53.41	-2.68
		5302003	55.77	45.99	**-17.53**
		5402001	-	-	-
		5402002	56.06	55.36	-1.25
	Perak	4209093	-	49.16	-
		4311001	57.87	65.49	**13.17**
		4409091	46.91	45.28	-3.47
		4511111	-	-	-
		4708084	51.38	51.71	0.64
		4811075	46.01	50.91	**10.66**
		5210069	44.51	47.28	**6.23**
Central West	Perak	4010001	-	-	-
	Selangor	2917001	59.82	54.47	**-8.95**
		3117070	-	108.26	-
		3118102	-	96.55	-
		3411017	-	97.81	-
		3416002	66.13	68.52	3.61
		3516022	-	51.57	-
		3613004	57.60	50.42	**-12.46**
		3710006	-	54.47	-
	Kuala Lumpur	3116003	56.04	52.96	**-5.5**
		3116006	54.53	43.70	**-19.87**
		3216001	-	-	-
		3217001	53.36	54.20	1.57
		3217002	61.63	-	-

Regions	State	Stations	15-minute		
			Full Series	2nd series	Difference in %
Central West	Kuala Lumpur	3217003	44.50	42.55	-4.39
	Negeri Sembilan & Melaka	2719001	53.46	46.61	**-12.8**
		2722002	-	-	-
		2224038	62.79	35.49	**-43.48**
South-west	Johor	1437116	-	55.11	-
		1534002	60.23	63.24	**5**
		1737001	-	54.09	-
		2025001	139.94	172.30	**23.13**
Inland	Kelantan	4819027	70.30	86.29	**22.75**
	Pahang	3121143	54.74	70.50	**28.78**
		3519125	-	-	-
		3818054	67.88	35.95	**-47.05**
		4023001	-	55.79	-
	Johor	2330009	-	123.91	-
East Coast	Terengganu	4734079	-	-	-
		4929001	-	-	-
		5331048	57.50	44.07	**-23.36**
		5428001	49.55	60.40	**21.90**
		5428002	49.55	71.51	**44.32**
	Pahang	3228174	-	-	-
		3231163	46.82	47.06	0.5
		3533102	-	-	-
	Johor	1839196	86.78	68.23	**-21.37**
		2235163	64.34	79.45	**23.48**
	Kelantan	5718002	-	-	-

Table 6.B: 100-year design storm from durations of 30-minute (unit in mm)

Regions	State	Stations	30-minute		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	72.96	74.07	1.52
	Kedah	5704055	84.90	86.13	1.44
		5806066	-	82.09	-
		5808001	65.73	63.96	-2.7
		6108001	95.66	109.32	**14.28**
		6206035	78.63	77.33	-1.65
	Pinang	5302001	76.71	68.91	**-10.17**
		5302003	71.01	66.37	**-6.53**
		5402001	-	-	-
		5402002	62.58	64.27	2.7
	Perak	4209093	96.70	89.74	**-7.20**
		4311001	85.12	92.80	**9.02**
		4409091	70.88	72.21	1.89
		4511111	-	-	-
		4708084	62.89	64.36	2.33
		4811075	71.41	79.78	**11.73**
		5210069	61.65	71.22	**15.53**
Central West	Perak	4010001	-	-	-
	Selangor	2917001	78.30	85.43	**9.10**
		3117070	80.82	93.43	**15.61**
		3118102	109.60	87.09	**-20.53**
		3411017	89.08	108.81	**22.15**
		3416002	68.75	69.23	0.71
		3516022	94.62	64.41	**-31.93**
		3613004	85.50	89.38	4.53
		3710006	101.36	81.06	**-20.03**
	Kuala Lumpur	3116003	73.27	75.57	3.14
		3116006	85.81	82.93	-3.35
		3216001	-	-	-
		3217001	-	103.50	-
		3217002	105.77	95.26	**-9.94**
		3217003	66.98	74.93	**11.86**
	Negeri Sembilan & Melaka	2719001	74.20	75.83	2.2
		2722002	-	-	-
		2224038	71.66	72.56	1.25

Regions	State	Stations	30-minute		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	75.96	83.89	**10.45**
		1534002	68.53	67.76	-1.11
		1737001	-	72.39	-
		2025001	127.76	-	-
Inland	Kelantan	4819027	72.56	75.45	3.99
	Pahang	3121143	73.65	77.53	**5.27**
		3519125	-	-	-
		3818054	72.49	-	-
		4023001	97.41	-	-
	Johor	2330009	-	123.65	-
East Coast	Terengganu	4734079	-	-	-
		4929001	-	-	-
		5331048	71.23	64.29	**-9.74**
		5428001	68.40	68.27	-0.19
		5428002	65.73	83.02	**26.3**
	Pahang	3228174	-	-	-
		3231163	75.61	74.40	-1.6
		3533102	97.66	122.71	**25.65**
	Johor	1839196	96.42	88.25	**-8.47**
		2235163	81.26	85.76	**5.53**
	Kelantan	5718002	-	-	-

Table 6.C: 100-year design storm from durations of 1-hour (unit in mm)

Regions	State	Stations	1-hour		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	101.68	97.33	-4.28
	Kedah	5704055	119.66	121.10	1.2
		5806066	-	123.67	-
		5808001	86.08	84.53	-1.8
		6108001	144.88	169.68	**17.12**
		6206035	97.57	101.84	4.38
	Pinang	5302001	116.05	106.33	**-8.37**
		5302003	100.22	94.71	**-5.5**
		5402001	136.05	162.96	**19.78**
		5402002	89.75	90.68	1.04
	Perak	4209093	133.12	131.82	-0.98
		4311001	116.86	119.71	2.44
		4409091	90.56	97.09	**7.21**
		4511111	-	-	-
		4708084	93.38	99.77	**6.84**
		4811075	97.33	86.21	**-11.43**
		5210069	82.43	91.31	**10.76**
Central West	Perak	4010001	-	174.97	-
	Selangor	2917001	102.15	109.77	**7.45**
		3117070	112.30	119.54	**6.44**
		3118102	132.25	97.13	**-26.56**
		3411017	129.13	170.79	**32.26**
		3416002	93.42	98.56	**5.5**
		3516022	123.00	107.77	**-12.39**
		3613004	112.56	121.56	**7.99**
		3710006	102.88	109.77	**6.7**
	Kuala Lumpur	3116003	112.50	121.60	**8.09**
		3116006	111.88	102.32	**-8.54**
		3216001	132.85	186.74	**40.57**
		3217001	104.93	116.90	**11.4**
		3217002	150.63	116.15	**-22.89**
		3217003	101.89	112.67	**10.57**
	Negeri Sembilan & Melaka	2719001	101.14	124.13	**22.73**
		2722002	-	-	**--**
		2224038	105.90	120.80	**14.06**

Regions	State	Stations	1-hour		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	108.25	122.95	**13.58**
		1534002	97.82	90.25	**-7.74**
		1737001	-	91.68	-
		2025001	138.98	161.35	**16.09**
Inland	Kelantan	4819027	92.12	98.17	**6.58**
	Pahang	3121143	99.67	110.36	**10.72**
		3519125	-	-	-
		3818054	91.47	98.01	**7.15**
		4023001	127.50	100.36	**-21.29**
	Johor	2330009	104.33	140.70	**34.86**
East Coast	Terengganu	4734079	-	-	-
		4929001	-	-	-
		5331048	106.57	105.46	-1.04
		5428001	86.08	109.51	**27.22**
		5428002	86.08	151.51	**76.02**
	Pahang	3228174	-	-	-
		3231163	113.68	113.03	-0.57
		3533102	139.20	153.70	**10.42**
	Johor	1839196	126.79	147.75	**16.54**
		2235163	99.70	109.13	**9.46**
	Kelantan	5718002	-	-	-

Table 6.D: 100-year design storm from durations of 3-hour (unit in mm)

Regions	State	Stations	3-hour		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	161.79	152.60	**-5.68**
	Kedah	5704055	233.79	160.05	**-31.54**
		5806066	162.02	127.02	**-21.60**
		5808001	180.46	171.26	**-5.1**
		6108001	215.42	291.99	**35.54**
		6206035	124.81	129.42	3.7
	Pinang	5302001	204.52	202.00	-1.23
		5302003	185.18	127.69	**-31.04**
		5402001	242.99	308.67	**27.03**
		5402002	172.71	131.39	**-23.92**
	Perak	4209093	185.09	143.10	**-22.69**
		4311001	148.78	-	-
		4409091	121.87	119.48	-1.96
		4511111	188.17	-	-
		4708084	122.41	108.68	**-11.21**
		4811075	151.15	148.49	-1.76
		5210069	120.00	107.70	**-10.25**
Central West	Perak	4010001	164.79	164.19	-0.37
	Selangor	2917001	148.96	144.95	-2.69
		3117070	147.70	164.54	**11.4**
		3118102	-	113.42	-
		3411017	188.13	214.06	**13.79**
		3416002	163.05	160.82	-1.37
		3516022	143.55	152.67	**6.35**
		3613004	140.33	134.56	-4.11
		3710006	119.07	144.95	**21.74**
	Kuala Lumpur	3116003	159.83	172.07	**7.66**
		3116006	130.81	129.87	-0.71
		3216001	160.27	178.49	**11.37**
		3217001	-	144.12	-
		3217002	166.28	141.98	**-14.61**
		3217003	129.25	135.00	4.45
	Negeri Sembilan & Melaka	2719001	132.27	134.39	1.6
		2722002	155.16	179.28	**15.55**
		2224038	135.88	124.93	**-8.06**

Regions	State	Stations	3-hour		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	153.14	178.91	**16.83**
		1534002	142.29	156.61	**10.06**
		1737001	-	142.10	-
		2025001	186.22	195.11	4.78
Inland	Kelantan	4819027	112.39	117.94	4.93
	Pahang	3121143	128.12	142.92	**11.55**
		3519125	-	-	-
		3818054	131.36	133.65	1.74
		4023001	184.02	127.74	**-30.58**
	Johor	2330009	136.11	155.16	**13.99**
East Coast	Terengganu	4734079	-	-	-
		4929001	223.14	244.96	**9.78**
		5331048	256.49	245.52	-4.28
		5428001	180.46	224.30	**24.29**
		5428002	180.46	278.67	**54.42**
	Pahang	3228174	-	-	-
		3231163	152.59	151.64	-0.62
		3533102	212.16	219.77	3.59
	Johor	1839196	167.36	189.40	**13.17**
		2235163	175.45	180.07	2.63
	Kelantan	5718002	-	-	-

Table 6.E: 100-year design storm from durations of 6-hour (unit in mm)

Regions	State	Stations	6-hour		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	158.90	164.30	3.4
	Kedah	5704055	331.48	257.07	**-22.45**
		5806066	178.94	121.61	**32.04**
		5808001	168.80	181.29	**7.4**
		6108001	235.19	318.31	**35.34**
		6206035	127.97	134.02	4.73
	Pinang	5302001	227.50	197.27	**-13.29**
		5302003	217.41	133.92	**-38.4**
		5402001	231.49	256.38	**10.75**
		5402002	192.69	167.70	**-12.97**
	Perak	4209093	179.35	148.25	**-17.34**
		4311001	180.71	182.37	0.92
		4409091	134.57	117.37	**-12.78**
		4511111	234.74	195.56	**-16.69**
		4708084	129.25	129.42	0.13
		4811075	164.04	151.33	**-7.74**
		5210069	147.69	163.26	**10.54**
Central West	Perak	4010001	175.43	164.92	**-5.99**
	Selangor	2917001	172.38	186.16	**7.99**
		3117070	150.40	165.04	**9.73**
		3118102	191.76	132.55	**-30.88**
		3411017	193.89	216.76	**11.79**
		3416002	209.98	163.85	**-21.97**
		3516022	173.49	190.91	**10.04**
		3613004	171.71	177.79	3.54
		3710006	127.35	186.16	**46.18**
	Kuala Lumpur	3116003	229.65	297.93	**29.73**
		3116006	141.62	140.59	-0.73
		3216001	190.01	185.49	-2.38
		3217001	151.30	149.50	-1.19
		3217002	-	137.95	-
		3217003	141.97	145.02	2.15
	Negeri Sembilan & Melaka	2719001	143.13	142.95	-0.13
		2722002	193.17	182.23	**-5.66**
		2224038	133.11	128.84	-3.21

Regions	State	Stations	6-hour		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	198.04	203.82	2.92
		1534002	192.42	188.48	-2.05
		1737001	278.17	211.69	**-23.90**
		2025001	219.13	191.57	**-12.58**
Inland	Kelantan	4819027	140.29	136.49	-2.71
	Pahang	3121143	147.91	170.71	**15.41**
		3519125	-	-	-
		3818054	137.95	128.86	**-6.59**
		4023001	221.07	130.21	**-41.1**
	Johor	2330009	179.85	211.42	**17.56**
East Coast	Terengganu	4734079	-	-	-
		4929001	297.40	392.02	**31.82**
		5331048	362.14	356.37	-1.59
		5428001	168.80	325.79	**93.01**
		5428002	168.80	320.94	**90.14**
	Pahang	3228174	-	-	-
		3231163	200.47	191.20	-4.63
		3533102	372.11	338.44	-9.05
	Johor	1839196	287.95	289.40	0.5
		2235163	-	196.86	-
	Kelantan	5718002	-	-	-

Table 6.F: 100-year design storm from durations of 12-hour (unit in mm)

Regions	State	Stations	12-hour		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	155.60	151.76	-2.47
	Kedah	5704055	378.20	369.30	-2.35
		5806066	185.63	176.63	-4.85
		5808001	200.60	231.68	**15.49**
		6108001	253.40	334.79	**32.12**
		6206035	148.88	156.25	4.95
	Pinang	5302001	276.05	-	-
		5302003	257.29	184.80	**-28.17**
		5402001	253.60	286.96	**13.16**
		5402002	269.85	259.05	-4
	Perak	4209093	191.14	159.75	**-16.42**
		4311001	180.44	179.25	-0.66
		4409091	121.92	114.46	**-6.12**
		4511111	232.24	190.92	**-17.79**
		4708084	132.77	129.31	-2.61
		4811075	215.66	160.15	**-25.74**
		5210069	164.73	179.37	**8.89**
Central West	Perak	4010001	228.05	225.33	-1.19
	Selangor	2917001	190.85	221.23	**15.92**
		3117070	145.94	152.43	4.45
		3118102	199.58	143.24	**-28.23**
		3411017	222.64	226.93	1.92
		3416002	216.69	180.54	**-16.68**
		3516022	190.04	211.71	**11.40**
		3613004	273.19	367.87	**34.66**
		3710006	129.92	221.23	**70.28**
	Kuala Lumpur	3116003	-	-	-
		3116006	148.74	149.67	0.62
		3216001	201.85	175.00	**-13.3**
		3217001	153.50	147.25	-4.07
		3217002	-	135.00	-
		3217003	171.17	156.51	**-8.57**
	Negeri Sembilan & Melaka	2719001	143.82	143.76	-0.04
		2722002	184.23	188.54	2.34
		2224038	148.43	151.03	1.75

Regions	State	Stations	12-hour		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	247.73	249.61	0.76
		1534002	211.54	179.52	**-15.14**
		1737001	320.24	268.45	**-16.17**
		2025001	229.53	193.45	**-15.72**
Inland	Kelantan	4819027	147.88	142.24	-3.81
	Pahang	3121143	148.27	179.24	**20.89**
		3519125	-	-	-
		3818054	142.14	129.02	**-9.23**
		4023001	-	-	-
	Johor	2330009	245.00	295.05	**20.43**
East Coast	Terengganu	4734079	-	-	-
		4929001	466.99	611.09	**30.86**
		5331048	449.89	495.79	**10.20**
		5428001	200.60	349.98	**74.47**
		5428002	-	372.44	-
	Pahang	3228174	-	-	-
		3231163	290.58	236.56	**-18.59**
		3533102	491.50	446.07	**-9.24**
	Johor	1839196	433.97	-	-
		2235163	-	222.33	-
	Kelantan	5718002	516.93	654.71	**26.65**

Table 6.G: 100-year design storm from durations of 1-day (unit in mm)

Regions	State	Stations	1-day		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	182.37	208.70	**14.44**
	Kedah	5704055	436.14	470.06	**7.78**
		5806066	223.43	213.57	-4.41
		5808001	233.73	258.47	**10.59**
		6108001	289.99	314.27	**8.37**
		6206035	208.88	222.99	**6.75**
	Pinang	5302001	327.13	-	-
		5302003	343.29	252.93	**-26.32**
		5402001	332.85	342.71	2.96
		5402002	380.50	409.21	**7.54**
	Perak	4209093	186.07	154.08	**-17.2**
		4311001	226.45	244.83	**8.12**
		4409091	157.95	123.68	**-21.69**
		4511111	245.73	260.23	**5.9**
		4708084	143.62	130.59	**-9.07**
		4811075	211.50	151.46	**-28.39**
		5210069	156.86	179.57	**14.48**
Central West	Perak	4010001	276.68	258.30	**-6.64**
	Selangor	2917001	208.67	216.48	3.74
		3117070	190.50	190.45	-0.03
		3118102	272.65	179.29	**-34.24**
		3411017	207.60	228.37	**10.01**
		3416002	227.82	176.70	**-22.44**
		3516022	203.85	227.65	**11.68**
		3613004	-	-	-
		3710006	141.30	216.48	**53.2**
	Kuala Lumpur	3116003	-	-	-
		3116006	200.22	215.44	**7.61**
		3216001	199.20	233.72	**17.33**
		3217001	154.63	146.94	-4.98
		3217002	-	159.91	-
		3217003	230.89	158.24	**-31.47**
	Negeri Sembilan & Melaka	2719001	152.26	156.87	3.03
		2722002	189.85	218.17	**14.91**
		2224038	171.70	186.49	**8.61**

Regions	State	Stations	1-day		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	-	-	-
		1534002	288.33	245.15	**-14.98**
		1737001	358.68	318.20	**-11.29**
		2025001	238.75	205.58	**-13.89**
Inland	Kelantan	4819027	209.94	212.80	1.36
	Pahang	3121143	172.79	175.39	1.50
		3519125	-	-	-
		3818054	147.36	143.64	-2.52
		4023001	283.34	148.73	**-47.51**
	Johor	2330009	340.40	431.37	**26.73**
East Coast	Terengganu	4734079	-	-	-
		4929001	702.29	913.06	**30.01**
		5331048	627.23	654.45	4.34
		5428001	228.67	439.33	**92.13**
		5428002	233.73	410.18	**75.5**
	Pahang	3228174	-	-	-
		3231163	445.24	445.81	0.13
		3533102	594.20	552.63	**-7**
	Johor	1839196	567.17	686.32	**21.01**
		2235163	-	316.24	-
	Kelantan	5718002	572.40	647.21	**13.07**

Table 6.H: 100-year design storm from durations of 3-day (unit in mm)

Regions	State	Stations	3-day		
			Full Series	2nd series	Difference in %
North-west	Perlis	6401002	292.45	267.85	**-8.41**
	Kedah	5704055	656.41	718.08	**9.39**
		5806066	344.83	400.69	**16.2**
		5808001	294.25	316.04	**7.41**
		6108001	369.69	439.44	**18.87**
		6206035	302.16	325.60	**7.76**
	Pinang	5302001	469.78	459.73	-2.14
		5302003	434.67	465.19	**7.02**
		5402001	516.29	524.04	1.5
		5402002	479.29	600.65	**25.32**
	Perak	4209093	211.99	199.90	**-5.71**
		4311001	-	501.36	-
		4409091	178.05	179.29	0.69
		4511111	261.46	272.36	4.17
		4708084	173.52	169.74	-2.18
		4811075	278.22	-	-
		5210069	221.31	236.23	**6.74**
Central West	Perak	4010001	350.24	382.80	**9.3**
	Selangor	2917001	286.90	294.94	2.8
		3117070	266.98	281.40	**5.4**
		3118102	322.37	255.03	**-20.89**
		3411017	234.85	255.68	**8.87**
		3416002	296.01	285.13	-3.67
		3516022	269.59	269.05	-0.2
		3613004	-	-	-
		3710006	214.80	289.95	**34.99**
	Kuala Lumpur	3116003	-	-	-
		3116006	248.32	252.62	1.73
		3216001	256.27	261.83	2.17
		3217001	224.56	233.47	3.97
		3217002	-	208.61	-
		3217003	311.29	217.97	**-29.98**
	Negeri Sembilan & Melaka	2719001	220.08	231.87	**5.36**
		2722002	239.94	205.00	**-14.56**
		2224038	305.85	379.39	**24.04**

Regions	State	Stations	3-day		
			Full Series	2nd series	Difference in %
South-west	Johor	1437116	465.16	643.00	**38.23**
		1534002	352.09	310.45	**-11.83**
		1737001	405.98	379.13	**-6.61**
		2025001	290.66	249.18	**-14.27**
Inland	Kelantan	4819027	389.01	270.67	**-30.42**
	Pahang	3121143	228.98	273.88	**19.61**
		3519125	-	-	-
		3818054	198.10	189.55	-4.32
		4023001	-	205.02	-
	Johor	2330009	643.67	726.67	**12.89**
East Coast	Terengganu	4734079	1041.86	-	-
		4929001	1155.79	1039.49	**-10.06**
		5331048	1116.67	804.53	**-27.95**
		5428001	298.52	727.42	**143.68**
		5428002	298.51	701.21	**134.90**
	Pahang	3228174	-	-	-
		3231163	628.54	763.03	**21.40**
		3533102	876.06	822.99	**-6.06**
	Johor	1839196	653.15	787.05	**20.5**
		2235163	617.74	600.97	-2.71
	Kelantan	5718002	741.19	792.66	**6.94**

APPENDIX 7: SAMPLE MOMENTS OF ANNUAL MAXIMUM RAINFALL SERIES

Table 7.A: Sample moments for 15 minutes annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	28.1	8.12	0.866	1.705	30.2	8.41	1.186	6.017	25.7	6.99	0.204	2.949
	5704055	37	29.8	9.13	0.035	0.263	24.8	9.23	0.574	4.117	34.1	6.40	1.126	6.237
	5806066	41	34.2	22.26	4.971	26.088	35.5	28.34	4.006	21.691	32.3	5.10	0.321	3.042
	5808001	30	29.4	7.8	0.178	0.198	30.1	10.63	-0.070	2.918	28.6	4.98	0.644	5.367
	6108001	37	33.1	10.21	1.022	1.19	34.6	9.88	0.235	2.470	32.1	10.89	1.680	7.670
	6206035	41	27.7	8.76	0.586	0.841	26.2	8.05	1.166	6.517	29.7	9.44	-0.070	2.981
	5302001	41	29.6	9.79	0.437	1.107	26.8	10.64	1.003	5.257	33.4	6.40	0.824	5.283
	5302003	36	29.1	9.7	0.595	0.578	29.1	11.74	0.678	3.601	28.5	6.56	0.043	2.772
	5402001	36	37.2	19.32	3.639	17.578	35.5	12.10	0.305	3.260	38.2	24.66	3.708	18.430
	5402002	36	29.9	8.15	0.479	0.392	26.7	8.33	1.070	5.035	33.5	5.81	1.425	6.344
	4209093	36	37.6	14.2	2.821	12.235	39.6	18.62	2.246	10.613	35.0	6.34	0.003	2.614
	4311001	37	38	8.95	-0.01	-0.34	34.2	9.20	0.498	3.180	42.6	6.07	0.977	3.950
	4409091	41	28.6	8.34	-0.015	-0.988	26.8	8.78	0.300	2.551	30.9	6.86	-0.149	3.218
	4511111	37	33.4	11.15	1.428	5.139	32.0	10.03	0.005	2.816	35.3	12.06	2.337	11.910
	4708084	37	27.2	7.82	0.934	1.556	27.3	7.02	0.531	2.589	27.0	8.63	1.242	6.853
	4811075	33	28.4	7.34	0.407	-0.531	26.4	9.15	0.198	3.263	29.6	6.32	0.548	2.937
	5210069	41	27.7	8.09	-0.245	-0.172	25.5	8.79	-0.006	2.822	30.6	6.13	0.330	3.045

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	36.7	25.87	3.425	13.028	32.7	21.12	2.911	13.564	42.1	30.17	3.683	18.325
	2917001	36	34.9	9.9	0.054	-0.388	33.4	11.60	0.243	2.569	36.0	7.28	0.511	4.973
	3117070	41	37.4	11.76	1.764	6.719	34.2	9.01	-0.430	4.531	41.0	13.72	2.535	11.001
	3118102	33	39	17.93	1.77	3.226	41.4	22.80	1.348	5.095	36.2	11.75	2.341	9.808
	3411017	41	33.5	13.78	2.126	5.397	31.7	12.81	1.696	7.711	35.2	15.12	2.590	11.955
	3416002	33	32.9	11.72	0.866	1.194	31.7	13.68	0.364	2.354	34.2	9.55	2.570	12.776
	3516022	41	32.3	16.21	2.548	8.928	29.5	20.55	2.664	11.498	35.8	4.81	1.401	7.175
	3613004	41	36.8	7.58	0.67	1.643	35.1	8.46	1.287	6.609	38.9	5.46	-0.092	3.234
	3710006	41	34.7	18.34	2.096	5.065	34.8	23.25	1.847	6.703	36.0	7.28	0.511	4.973
	3116003	36	35.6	7.51	0.056	0.391	33.2	7.93	1.346	5.913	37.8	6.12	0.191	4.086
	3116006	34	35	6.39	-0.253	0.641	33.3	7.86	0.293	3.701	36.9	3.41	-0.181	3.343
	3216001	39	34.6	20.65	6.055	29.744	30.3	9.12	-0.341	3.727	40.1	28.51	4.136	20.973
	3217001	39	32.8	9.37	-0.021	0.089	30.8	11.04	0.032	3.011	33.9	7.48	0.539	4.006
	3217002	39	33.6	9.34	1.418	-0.967	31.1	9.26	0.930	4.696	38.1	9.28	2.700	13.689
	3217003	37	31.2	8.47	-0.648	0.398	28.3	9.77	0.038	3.451	34.4	4.35	-0.409	3.000
	2719001	41	31.4	8.94	-0.013	0.516	32.4	10.69	0.355	3.745	34.5	3.99	0.595	3.622
	2722002	41	29.2	21.72	4.988	26.554	23.4	9.31	0.599	3.874	37.0	29.82	4.011	20.245
	2224038	41	31.4	8.65	1.295	1.552	32.7	10.74	0.817	3.512	29.0	3.11	-0.188	3.075
South West	1437116	41	27.5	11.79	-0.145	-1.169	27.2	10.69	-0.278	2.708	28.0	13.17	-0.145	2.223
	1534002	33	32.6	10.74	0.359	0.407	29.9	9.97	-0.064	2.691	35.4	10.89	0.481	4.572
	1737001	37	38.4	46.07	4.915	25.508	44.6	62.32	3.631	17.561	31.4	7.71	0.742	3.723
	2025001	37	40.2	23.5	2.994	10.716	38.9	18.11	1.646	7.652	40.8	28.45	3.303	15.300

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	33.5	10.74	1.914	6.187	32.4	9.30	1.455	5.199	35.3	12.28	2.090	9.069
	3121143	36	29.9	9.71	0.848	3.248	26.9	9.38	0.176	3.935	33.4	8.82	2.379	10.967
	3519125	39	32.6	35.86	4.411	20.726	27.2	22.38	1.809	5.627	38.8	46.68	4.176	21.215
	3818054	33	26.9	12.89	1.427	3.631	27.7	17.47	1.432	5.331	27.6	7.02	-1.464	7.396
	4023001	38	31.7	9.66	0.751	1.455	31.6	10.63	1.135	5.572	33.0	9.60	0.151	4.479
	2330009	41	31.4	16.31	3.374	15.283	28.5	9.79	0.682	4.150	35.2	21.68	3.066	14.842
East	5718002	31	44.3	47.91	3.574	12.118	29.4	9.97	0.523	3.017	56.2	61.37	2.642	9.359
	4734079	41	37.1	33.37	4.812	22.99	31.8	10.36	0.498	4.108	43.0	49.14	3.407	15.946
	4929001	36	37.3	19.74	4.014	19.904	32.3	9.42	1.021	4.538	42.5	25.43	3.463	16.777
	5331048	39	30.2	10.09	0.602	1.745	29.8	11.27	0.996	6.002	30.6	7.92	-0.622	3.768
	5428001	34	32.6	10.8	-0.071	-0.03	31.3	12.49	-0.048	2.953	34.5	8.96	0.193	4.752
	5428002	34	35.2	12.25	0.464	-0.638	32.5	11.31	0.860	4.344	37.5	12.67	0.242	2.654
	3228174	34	38.3	23.04	3.44	11.713	30.1	4.87	0.002	3.770	45.7	29.72	2.479	8.786
	3231163	38	33.7	5.18	0.243	-0.208	32.8	5.63	0.461	3.304	34.6	4.56	0.361	3.125
	3533102	37	29.9	13.53	2.753	11.685	24.4	8.54	1.307	6.275	36.2	15.19	3.117	15.515
	1839196	41	39.3	14.61	1.806	4.699	38.9	17.62	1.858	8.008	39.1	9.71	0.560	3.633
	2235163	32	34.1	9.75	1.673	5.352	32.5	7.82	0.285	5.506	35.0	11.16	1.979	9.015

Table 7.B: Sample moments for 30 minutes annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	38.8	11.39	0.973	1.374	41.6	10.31	1.034	4.609	35.8	11.74	1.376	7.447
	5704055	37	45.4	14.06	0.375	-0.646	38.8	11.48	0.336	3.690	51.5	13.42	0.179	2.294
	5806066	41	48.8	20.81	4.176	21.942	49.8	25.38	3.826	20.927	48.4	11.09	0.389	2.902
	5808001	30	41.3	8.72	0.457	0.758	41.8	8.93	0.053	4.737	40.5	8.84	0.867	5.106
	6108001	37	46	15.53	1.506	3.987	45.9	12.28	1.115	7.198	47.2	19.11	1.361	6.094
	6206035	41	40.4	13.97	0.314	-0.466	36.4	11.26	0.425	3.059	45.8	15.63	-0.242	2.206
	5302001	41	45.6	13.5	0.096	-0.943	41.7	13.95	0.676	3.023	50.9	10.80	-0.548	3.436
	5302003	36	41.1	11.5	0.27	-0.558	39.9	12.13	0.594	3.295	41.7	10.83	0.001	3.136
	5402001	36	51.8	18.34	2.711	11.109	49.5	10.35	0.788	4.860	53.7	23.81	2.428	11.267
	5402002	36	42.6	8.45	0.125	-0.742	38.4	7.84	0.661	2.653	46.6	6.68	0.553	3.771
	4209093	36	52.6	14.27	1.484	3.513	52.3	16.53	1.785	8.043	52.8	11.39	0.691	3.424
	4311001	37	53.4	12.52	0.356	-0.245	47.9	11.25	0.692	3.376	60.7	10.25	0.625	4.492
	4409091	41	39.9	11.86	0.328	-0.559	36.0	9.46	0.196	2.577	45.4	12.31	-0.071	2.792
	4511111	37	48.9	19	2.294	10.075	43.4	13.23	0.413	2.701	54.9	22.28	2.541	12.705
	4708084	37	37.6	10.65	0.155	-0.834	37.0	10.54	0.279	2.645	37.9	10.83	0.116	3.199
	4811075	33	42.3	10.27	0.899	0.215	39.0	9.44	0.308	4.875	44.6	11.46	0.591	3.190
	5210069	41	38.3	10.53	-0.028	-0.22	35.2	10.65	0.044	2.517	43.0	8.33	0.699	2.996

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	48	25.13	3.112	15.201	44.0	20.87	3.322	17.177	52.6	28.93	3.099	14.871
	2917001	36	46.7	12.4	0.389	0.09	42.3	11.94	0.629	3.616	51.4	10.71	0.756	5.102
	3117070	41	53.9	12.95	-0.013	0.449	50.1	11.62	-0.510	3.195	58.8	12.61	0.428	3.661
	3118102	33	52.3	15.22	1.202	1.47	52.0	18.54	1.463	5.404	52.4	11.58	0.442	2.647
	3411017	41	48.4	12.94	1.134	1.631	46.8	11.36	0.627	3.787	49.6	15.33	1.256	4.852
	3416002	33	45.1	10.41	0.05	-0.85	43.3	9.18	0.304	2.849	47.4	11.39	-0.355	2.909
	3516022	41	45.5	14.31	1.954	8.294	42.4	17.07	2.570	11.521	49.8	7.41	-0.304	2.784
	3613004	41	55.2	10.47	0.786	1.83	53.5	11.19	0.764	5.207	57.2	9.03	1.632	7.706
	3710006	41	46.7	17.67	1.117	3.754	44.4	20.29	1.449	6.394	51.4	10.71	0.756	5.102
	3116003	36	52.5	8.59	0.204	-0.059	49.8	7.25	0.014	3.452	55.4	8.72	0.082	3.850
	3116006	34	53	9.87	0.263	0.304	47.3	7.21	-0.621	4.100	59.7	8.62	0.446	2.212
	3216001	39	48.8	19.68	3.912	21.054	43.4	10.58	-0.159	5.504	56.3	25.47	3.605	17.873
	3217001	39	48.9	13.06	1.271	6.459	43.8	11.56	-0.618	3.050	53.8	14.14	2.150	9.832
	3217002	39	49.2	12.61	0.972	-0.179	45.9	17.47	2.935	14.144	57.5	11.04	1.581	8.641
	3217003	37	48.1	12.38	-0.729	0.583	41.5	11.69	-0.592	3.680	55.4	7.43	0.331	5.170
	2719001	41	43.9	11.85	0	-1.128	41.0	12.03	0.410	2.938	52.6	9.65	0.327	4.198
	2722002	41	42.8	23.5	4.042	21.611	35.4	11.65	-0.311	3.374	53.4	30.54	3.611	17.845
	2224038	41	45.4	9.55	0.571	0.545	44.8	10.95	0.613	3.784	44.9	7.68	0.670	2.663
South West	1437116	41	45.1	16	-0.305	-0.995	44.4	14.20	-0.682	2.987	46.2	18.13	-0.175	2.315
	1534002	33	43.7	11.07	0.015	-0.973	40.1	9.07	0.329	4.220	47.6	11.79	-0.618	2.743
	1737001	37	49.4	43.73	4.977	26.327	55.5	58.78	3.744	18.423	42.8	9.92	0.426	2.532
	2025001	37	53.4	20.88	2.677	9.49	53.1	16.89	0.930	4.653	53.6	24.61	3.348	16.048

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	48.6	10.17	0.238	0.137	47.4	8.80	0.376	3.126	50.9	11.76	-0.166	3.288
	3121143	36	44.4	12.56	0.118	-0.043	39.8	12.76	0.509	4.305	48.8	10.35	0.360	3.081
	3519125	39	48.7	67.65	5.781	32.243	36.3	18.55	1.778	5.859	63.1	96.93	4.189	21.291
	3818054	33	38.1	12.78	0.454	0.471	38.1	15.14	0.837	3.903	40.2	10.89	-0.361	5.169
	4023001	38	46.1	14.28	1.641	5.938	46.8	17.25	1.926	8.638	47.5	13.35	0.594	7.627
	2330009	41	40.3	16.36	2.298	12.357	36.9	9.63	-0.239	2.721	45.6	21.58	1.871	8.915
East	5718002	31	58.4	49.14	3.574	12.377	41.1	9.42	0.029	3.085	72.3	62.19	2.661	9.627
	4734079	41	54.3	64.97	5.927	32.243	44.2	11.38	1.264	8.121	66.5	97.34	4.018	20.211
	4929001	36	53.2	18.34	2.817	12.715	48.6	12.18	0.323	3.421	57.8	21.94	3.065	15.164
	5331048	39	43.7	13.38	-0.115	0.259	42.4	13.99	0.326	4.257	44.8	12.12	-0.722	3.910
	5428001	34	44.7	11.27	-0.142	-0.504	41.1	10.78	-0.125	3.010	48.6	10.60	-0.324	3.519
	5428002	34	48.2	14.27	-0.058	-0.772	45.0	12.63	0.023	2.464	50.7	15.25	-0.222	3.125
	3228174	34	55.2	30.9	3.962	17.773	45.6	8.14	-0.531	3.477	64.4	40.05	2.999	13.208
	3231163	38	51.5	10.09	0.191	0.763	50.0	11.03	0.392	4.580	53.0	8.55	0.217	3.358
	3533102	37	45	17.13	1.34	3.316	40.3	15.56	1.491	6.689	51.1	17.44	1.317	7.851
	1839196	41	52	14.28	1.283	3.014	48.9	15.08	2.059	9.729	55.4	12.53	0.421	4.467
	2235163	32	43.9	10.4	1.078	0.838	40.1	6.91	0.980	4.355	47.0	11.64	0.756	3.637

Table 7.C: Sample moments for 1 hour annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	53.3	15.15	0.84	0.549	57.3	13.75	1.177	5.585	48.5	15.32	1.149	4.541
	5704055	37	69	19.16	0.513	-0.071	61.6	15.59	0.639	3.294	75.6	19.46	0.222	3.932
	5806066	41	66.1	21.34	2.407	9.138	67.0	24.97	2.426	12.204	66.9	16.21	0.809	3.680
	5808001	30	56.2	11.73	0.325	-0.091	54.8	10.62	1.405	6.325	56.3	13.10	-0.091	2.967
	6108001	37	61.8	24	1.989	5.942	58.2	14.79	1.042	4.829	66.9	30.95	1.518	5.579
	6206035	41	56.7	16.06	0.049	-0.257	53.2	14.62	-0.149	3.046	60.8	17.02	0.077	2.873
	5302001	41	65.6	17.37	0.488	-0.582	61.8	17.90	0.925	3.759	70.0	15.77	-0.009	2.608
	5302003	36	58.5	15.57	0.348	-0.45	56.9	15.15	0.754	3.004	59.2	16.33	-0.015	3.665
	5402001	36	69.8	21.61	1.262	1.953	66.5	13.37	0.964	3.972	72.4	27.71	0.955	4.083
	5402002	36	60.3	11.9	0.259	-0.561	55.9	11.47	0.764	3.707	64.4	10.71	0.134	3.545
	4209093	36	70.7	19.65	0.879	-0.406	68.3	19.03	0.959	3.192	73.3	19.96	0.883	3.482
	4311001	37	72.7	16.8	0.354	-0.571	66.0	14.07	0.338	2.517	83.0	16.29	0.017	2.978
	4409091	41	55.5	14.26	0.3	-0.263	52.7	11.27	-0.076	3.286	60.4	16.57	-0.070	2.233
	4511111	37	68.7	28.51	3.064	14.569	60.9	18.67	1.944	9.096	76.2	35.05	2.887	14.152
	4708084	37	51.1	13.55	0.726	0.606	50.6	11.82	1.034	5.285	51.1	15.39	0.632	3.361
	4811075	33	56.8	14.05	0.7	0.614	54.6	14.93	1.505	6.618	58.1	13.26	-0.163	2.919
	5210069	41	52.3	12.34	0.152	0.122	49.7	12.39	-0.074	2.566	56.5	11.08	0.843	2.923

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	61.1	23.46	2.436	7.812	59.1	19.69	2.160	10.802	63.0	27.28	2.651	12.588
	2917001	36	63.7	15.41	0.33	-0.391	58.3	14.18	0.401	3.338	69.5	13.95	0.620	3.063
	3117070	41	73.6	17.1	0.091	-0.096	68.5	14.64	-0.277	3.116	80.9	17.19	0.006	2.617
	3118102	33	70.5	18.06	1.929	6.414	70.9	23.07	2.080	9.258	70.5	12.07	-0.067	2.459
	3411017	41	66.9	18.73	1.383	1.241	64.7	13.04	0.125	2.503	68.7	24.72	1.320	5.096
	3416002	33	61.4	13.04	0.095	-0.26	59.8	9.92	-0.245	3.133	64.1	16.02	-0.095	2.778
	3516022	41	65.7	17.19	0.523	-0.237	61.9	16.70	1.033	4.212	70.9	16.39	0.007	2.497
	3613004	41	74.5	13.35	0.726	0.129	72.9	13.86	0.772	3.667	76.2	12.46	0.998	4.478
	3710006	41	60.9	16.75	-0.163	2.128	60.1	18.86	-0.165	5.403	69.5	13.95	0.620	3.063
	3116003	36	72.2	14.81	1.112	2.731	69.7	11.32	-0.054	2.096	76.0	17.25	1.055	5.927
	3116006	34	69.9	13.79	0.195	-0.803	59.2	7.66	0.386	3.311	81.3	9.38	0.001	3.638
	3216001	39	65.8	20.59	2.029	7.721	62.2	17.97	0.373	3.373	72.5	23.80	2.656	11.688
	3217001	39	66.5	13.96	1.013	2.252	58.9	14.61	0.901	8.732	73.9	11.51	1.033	5.041
	3217002	39	65.5	15.77	0.557	-0.396	63.2	27.79	3.108	15.290	75.0	12.36	1.543	6.075
	3217003	37	67.1	17.54	-0.038	0.213	61.2	17.23	-0.086	3.275	74.1	14.44	0.665	5.133
	2719001	41	59	15.91	0.66	0.581	53.2	13.75	0.493	3.675	71.3	16.04	0.738	3.960
	2722002	41	57	23.73	2.754	14.393	48.3	13.49	-0.823	4.939	69.7	29.28	2.581	12.499
	2224038	41	60.2	14.34	0.517	0.787	57.2	13.42	0.190	3.732	63.1	15.05	0.968	3.834
South West	1437116	41	68	18.46	-0.026	-0.163	66.1	16.25	-0.640	4.090	70.6	20.81	0.194	3.078
	1534002	33	59	13.67	0.609	0.266	54.7	12.59	1.750	8.535	63.5	13.40	-0.215	3.799
	1737001	37	64.7	41.08	4.863	26.052	72.1	54.09	3.811	19.096	56.9	13.26	0.202	2.153
	2025001	37	70.6	19.02	1.919	5.344	70.9	17.18	0.581	3.464	70.1	20.88	2.936	14.008

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	65.7	12.03	0.029	-0.848	65.4	12.28	-0.039	2.908	66.5	11.87	0.030	2.532
	3121143	36	60.7	15.93	0.214	0.63	55.7	16.00	0.149	3.864	64.8	14.55	0.894	4.572
	3519125	39	64.2	79.79	5.924	33.495	50.1	15.09	0.758	4.282	80.3	115.92	4.144	21.014
	3818054	33	51.7	13	0.208	-0.022	53.5	12.79	0.070	4.189	53.2	15.97	0.652	4.211
	4023001	38	62.5	19.14	1.573	4.52	64.3	22.12	1.882	7.886	62.2	16.70	0.048	4.300
	2330009	41	53.1	17.09	1.379	5.076	50.8	12.05	0.237	3.243	56.9	21.88	1.169	4.993
East	5718002	31	76.1	54.7	3.473	11.927	55.5	10.76	1.025	5.955	92.6	68.62	2.600	9.492
	4734079	41	81.1	125.44	6.16	34.162	61.6	19.01	2.142	10.378	105.2	188.22	4.160	21.114
	4929001	36	74.4	25.53	3.308	16.136	69.4	15.94	0.057	4.576	80.0	31.56	3.373	16.834
	5331048	39	61.1	18.68	0.206	-0.49	59.1	18.39	0.492	3.343	62.3	18.79	0.061	3.021
	5428001	34	62.4	13.92	0.749	0.717	57.6	12.66	0.576	2.970	66.4	13.74	1.117	5.259
	5428002	34	67.1	20.32	0.724	0.762	62.8	14.20	-0.642	3.465	70.2	24.44	0.710	3.327
	3228174	34	74.9	50.17	4.879	26.197	61.6	9.98	-0.354	3.687	87.0	66.85	3.643	17.926
	3231163	38	71.5	15.03	0.51	0.369	68.4	15.96	0.706	4.211	74.1	13.77	0.649	3.625
	3533102	37	64.4	23.31	1	1.127	58.7	22.56	1.535	6.046	71.6	22.42	0.654	4.883
	1839196	41	68.4	18.37	0.93	1.651	65.3	17.08	0.750	5.006	71.6	19.83	1.138	4.867
	2235163	32	60.4	12.21	1.365	2.587	57.7	8.46	-0.323	3.471	62.4	14.26	1.415	5.136

Table 7.D: Sample moments for 3 hour annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	76.3	22.77	1.018	0.551	82.1	22.91	0.926	3.740	68.5	20.95	1.510	6.480
	5704055	37	109.2	34.2	1.412	2.556	106.3	43.80	1.835	6.516	110.3	24.07	-0.189	1.960
	5806066	41	86.9	23.85	1.255	1.195	90.1	27.30	1.141	4.252	83.9	17.13	0.304	2.530
	5808001	30	78.2	27.61	1.953	4.493	77.5	29.56	2.166	9.535	76.5	27.76	1.770	8.748
	6108001	37	83.9	31.21	2.097	7.641	77.8	17.68	0.446	2.787	91.0	40.23	1.678	5.722
	6206035	41	77.2	19.78	0.165	-0.509	74.1	21.21	0.269	2.747	79.3	18.02	0.369	3.098
	5302001	41	100.2	30.88	0.803	-0.041	96.5	30.81	1.039	3.938	102.3	31.21	0.720	3.516
	5302003	36	82.4	27.99	1.871	4.866	86.9	33.12	1.792	7.144	76.5	18.63	0.577	3.844
	5402001	36	100.8	36.06	1.666	3.54	100.3	26.24	0.876	3.932	98.8	44.31	1.902	7.257
	5402002	36	88	21.69	1.328	1.747	88.4	25.89	1.428	4.794	85.9	15.49	0.489	3.562
	4209093	36	90.4	25.74	1.439	2.381	90.1	31.16	1.550	5.743	90.6	18.34	0.713	3.123
	4311001	37	100.4	19.69	0.291	0.418	92.8	16.47	0.053	3.116	109.4	19.11	0.224	4.594
	4409091	41	72.4	15.93	0.201	0.052	72.0	19.39	0.858	4.618	75.1	15.41	0.333	3.653
	4511111	37	88	29.26	1.882	6.038	82.6	27.29	1.038	4.179	92.2	31.48	2.610	13.032
	4708084	37	65.6	16.15	0.834	0.209	64.3	17.14	1.287	4.494	66.3	15.20	0.373	3.113
	4811075	33	72.3	24.9	1.286	1.854	71.5	25.96	1.800	7.035	74.1	23.99	0.685	4.580
	5210069	41	69.1	18.97	0.576	0.023	67.6	21.69	0.773	3.694	72.0	13.43	0.088	2.617

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	80.5	27.38	0.98	0.81	77.5	29.52	0.898	3.644	82.2	24.00	1.779	9.234
	2917001	36	88.2	22.85	0.466	0.683	78.6	22.32	1.358	7.877	96.8	19.24	0.259	3.414
	3117070	41	91.4	19.48	0.585	0.242	86.5	16.88	0.178	2.499	98.7	21.16	0.601	3.468
	3118102	33	86.9	26.08	2.646	9.626	91.7	35.71	1.974	8.099	84.4	13.38	0.160	5.345
	3411017	41	90.1	31.5	1.078	-0.166	89.6	26.03	0.783	3.412	89.9	37.87	1.253	4.939
	3416002	33	87.1	21.94	0.975	2.436	88.3	26.60	1.163	6.067	89.2	21.55	0.767	4.817
	3516022	41	89.4	21.03	0.405	-0.785	88.2	18.65	0.332	2.363	91.0	23.78	0.390	3.242
	3613004	41	91.8	17.33	0.441	-0.423	89.7	16.59	0.983	4.321	93.6	18.50	-0.045	2.910
	3710006	41	77.2	19.75	-0.157	1.647	77.8	24.12	-0.192	4.499	96.8	19.24	0.259	3.414
	3116003	36	87.8	21.49	1.312	3.233	86.4	19.49	0.905	4.146	92.2	24.95	1.258	6.661
	3116006	34	86.6	17.21	0.268	-0.539	75.1	12.15	0.077	2.444	97.6	14.66	-0.063	2.819
	3216001	39	82.7	22.97	1.722	4.113	80.1	23.21	1.838	9.189	87.0	22.54	1.708	7.172
	3217001	39	88.7	18.89	1.535	3.342	83.4	22.65	1.207	8.061	92.0	16.05	1.162	4.458
	3217002	39	85.8	19.84	0.341	-0.647	86.3	28.80	1.730	7.823	91.9	18.64	0.260	2.475
	3217003	37	87.9	19.73	-0.177	-0.415	82.8	19.71	-0.128	2.835	92.3	18.39	0.090	3.566
	2719001	41	77.7	18.27	0.769	0.995	72.4	18.26	1.419	8.093	87.5	16.35	0.497	2.851
	2722002	41	69.3	23.76	2.073	8.527	60.2	14.40	0.623	5.604	84.2	27.96	1.733	8.478
	2224038	41	76.1	18.99	0.316	0.241	74.6	20.43	0.266	3.486	76.6	16.81	0.827	3.049
South West	1437116	41	90.9	23.74	0.366	0.629	85.9	21.31	-0.508	4.126	97.0	25.31	0.987	4.554
	1534002	33	84	20.32	0.681	0.632	80.2	18.64	0.494	3.679	86.7	21.39	0.842	4.740
	1737001	37	86.9	39.5	3.941	19.274	90.1	50.70	3.498	17.545	82.5	20.24	0.704	3.298
	2025001	37	95.6	29.38	0.665	-0.255	96.3	30.22	0.311	2.334	93.6	28.76	1.288	5.690

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	80.9	14.44	-0.046	-0.737	81.0	14.39	-0.297	2.937	81.7	14.94	0.144	2.969
	3121143	36	74.6	21.59	0.23	0.25	68.4	21.80	0.143	3.270	79.1	20.34	0.842	4.143
	3519125	39	89.4	76.75	5.656	31.673	73.5	19.80	0.156	2.339	108.3	109.47	4.084	20.668
	3818054	33	73.4	17.3	1.141	2.232	77.9	17.48	1.597	8.039	71.9	18.64	0.769	3.714
	4023001	38	86.4	30.05	0.993	1.419	92.9	34.09	0.965	3.530	79.6	22.48	-0.107	4.811
	2330009	41	73.6	21.62	0.434	-0.312	71.6	19.24	0.180	2.791	76.0	24.26	0.551	2.916
East	5718002	31	107.2	67.07	3.205	10.606	84.9	16.08	0.092	2.830	125.5	84.82	2.350	8.646
	4734079	41	116.2	122.2	5.798	31.287	98.9	31.15	1.829	7.348	138.3	181.24	4.062	20.514
	4929001	36	109.4	37.15	0.933	0.566	99.4	30.35	0.611	4.516	117.7	41.18	1.016	3.404
	5331048	39	105.4	37.92	1.411	2.058	105.5	38.21	1.342	4.784	102.2	37.63	1.765	7.990
	5428001	34	96.9	30.6	0.837	0.202	89.8	25.95	0.567	3.299	103.3	33.05	0.881	3.632
	5428002	34	102	37.73	2.098	7.344	89.3	24.14	0.530	3.662	113.7	43.71	2.074	9.781
	3228174	34	100.1	90.39	5.443	30.88	82.4	16.82	0.022	3.546	114.6	122.98	4.049	20.434
	3231163	38	89.2	19.74	0.789	-0.117	83.5	19.48	1.133	4.236	95.6	17.88	1.005	5.352
	3533102	37	105.2	35.09	0.504	-1.051	99.2	35.70	0.846	3.025	112.7	33.05	0.188	2.147
	1839196	41	93.7	26.53	0.6167	0.395	92.5	27.29	0.118	2.979	93.1	27.10	1.369	6.138
	2235163	32	89.5	24.74	1.465	2.84	88.3	23.88	2.192	10.512	89.0	26.23	1.135	5.420

Table 7.E: Sample moments for 6 hour annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	83.4	24.98	0.917	0.419	87.8	24.74	0.679	2.959	76.9	24.90	1.468	7.002
	5704055	37	140.7	50.28	1.351	2.168	142.2	61.21	1.551	5.998	137.0	40.33	0.670	3.610
	5806066	41	93.8	24.41	1.389	1.836	96.3	28.69	1.282	4.649	91.0	15.41	-0.221	2.794
	5808001	30	86.1	27.88	1.883	3.437	87.5	29.36	1.784	6.802	82.6	28.82	1.814	8.540
	6108001	37	93.2	35.15	1.859	6.11	85.8	19.60	0.040	2.407	101.2	45.34	1.466	5.211
	6206035	41	85.1	21.21	-0.295	-0.655	80.2	21.39	-0.301	2.802	88.6	21.57	-0.150	2.440
	5302001	41	120.6	37.06	0.911	1.214	118.2	40.25	1.340	5.409	120.5	33.10	0.001	2.715
	5302003	36	93.7	35.25	2.455	9.346	101.2	42.43	2.273	10.371	83.8	20.20	0.189	2.955
	5402001	36	116.6	37.14	1.14	1.791	117.7	26.32	0.416	3.854	113.1	45.92	1.445	5.385
	5402002	36	103.7	26.08	0.723	-0.278	101.9	30.61	0.868	3.117	103.6	19.87	0.715	3.319
	4209093	36	97.5	25.78	1.018	1.312	98.8	29.93	1.146	4.990	96.9	20.65	0.274	2.567
	4311001	37	109.4	22.44	0.623	0.482	99.7	16.73	0.614	4.076	120.2	22.62	0.353	4.705
	4409091	41	77.1	15.88	-0.182	0.153	76.8	20.27	0.595	4.657	79.8	13.98	0.274	3.858
	4511111	37	96.4	36.54	1.795	3.756	94.9	41.23	1.667	6.412	95.9	31.79	2.254	11.321
	4708084	37	71.6	18.68	0.715	0.126	69.9	18.66	1.002	4.319	73.0	18.63	0.558	3.874
	4811075	33	77.8	27.9	1.25	1.577	78.5	29.21	1.773	6.322	77.7	26.47	0.634	4.542
	5210069	41	76	22.89	0.909	0	72.1	21.74	0.940	3.907	81.6	22.67	1.058	4.530

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	88.8	30.12	0.756	0.959	85.3	33.05	0.937	4.317	90.7	25.53	0.848	5.555
	2917001	36	95.3	27.46	0.659	0.809	84.8	26.71	1.273	6.925	104.7	24.19	0.818	4.017
	3117070	41	95.6	18.52	0.432	0.218	90.5	15.89	-0.011	2.521	103.7	20.86	0.378	3.052
	3118102	33	91.4	27.96	2.19	6.015	97.7	38.05	1.498	5.548	88.2	16.19	1.114	7.782
	3411017	41	95.2	32.94	1.128	0.47	95.3	28.56	0.948	4.340	94.1	38.30	1.343	4.992
	3416002	33	99.5	30.89	2.192	7.974	100.9	38.73	2.388	11.271	100.7	24.38	0.387	2.686
	3516022	41	97.8	27.08	0.67	-0.004	92.2	18.89	0.136	2.488	105.2	33.76	0.329	2.485
	3613004	41	100.4	24.52	0.694	-0.546	94.3	20.58	1.268	4.954	107.3	27.67	0.165	2.712
	3710006	41	80.9	17.98	0.234	0.996	81.6	22.19	0.158	3.695	104.7	24.19	0.818	4.017
	3116003	36	97.2	33.22	2.412	7.778	91.6	20.32	0.679	3.047	105.1	42.23	1.997	8.119
	3116006	34	91.5	19	0.243	-0.618	79.2	13.70	0.349	2.514	103.3	15.69	0.053	3.049
	3216001	39	90.5	23.84	1.496	1.918	89.4	24.53	1.702	6.330	92.7	22.98	1.287	5.225
	3217001	39	93.1	19.78	1.139	1.742	89.4	24.26	0.846	5.661	94.4	16.16	0.797	3.708
	3217002	39	92	20.86	-0.062	-1.197	93.8	35.97	2.430	12.064	98.3	19.27	-0.198	2.530
	3217003	37	94.2	21.14	-0.045	-0.861	89.4	20.16	0.066	2.471	98.1	21.15	-0.025	3.127
	2719001	41	85.3	19.81	0.705	0.782	79.3	20.49	1.673	8.496	93.9	15.04	0.985	3.884
	2722002	41	74.3	27.29	1.907	4.279	65.6	22.14	3.194	15.892	89.2	28.79	1.321	6.446
	2224038	41	81.5	21.04	0.219	-0.326	80.9	23.88	0.218	2.822	80.5	16.61	0.548	2.755
South West	1437116	41	100.2	29.38	0.798	1.022	93.2	25.49	0.398	3.737	108.6	31.99	1.007	4.005
	1534002	33	92.9	27.68	1.21	1.662	90.8	30.43	1.460	6.437	93.8	25.19	1.169	5.185
	1737001	37	101.6	43.8	2.535	8.722	104.7	53.14	2.565	11.398	96.7	30.21	0.926	3.949
	2025001	37	104.8	36.11	0.804	0.062	108.1	41.93	0.692	3.073	99.5	28.38	0.812	4.742

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	88.1	18.52	0.544	1.788	87.0	18.09	0.871	5.966	90.2	19.18	0.079	2.893
	3121143	36	81.9	23.51	0.651	0.826	75.3	20.37	-0.029	3.268	86.4	26.18	0.926	3.950
	3519125	39	98.8	76.02	5.487	30.095	83.0	22.02	0.300	2.801	117.5	107.87	4.018	20.226
	3818054	33	81.1	16.5	1.001	1.533	84.0	18.38	1.142	5.234	81.3	16.92	0.652	4.267
	4023001	38	92.7	37.18	2.046	6.648	101.5	44.70	1.781	7.334	82.8	21.49	-0.039	5.565
	2330009	41	86	29.19	0.558	-0.357	80.8	25.20	0.622	3.523	92.1	32.92	0.385	2.428
East	5718002	31	126.3	66.7	2.692	7.84	107.6	26.82	0.794	3.982	140.7	83.81	2.079	7.478
	4734079	41	149.6	126.15	4.701	22.692	132.6	60.01	2.891	13.744	169.5	177.97	3.727	18.491
	4929001	36	140.7	54.4	0.326	-0.621	123.7	47.32	0.371	3.114	153.6	58.35	0.248	2.592
	5331048	39	144.3	57.71	1.519	2.488	145.3	59.18	1.260	4.850	138.0	56.11	2.171	10.144
	5428001	34	135.5	56.03	0.894	0.589	126.9	55.46	1.215	5.722	142.4	55.72	0.816	4.031
	5428002	34	135.2	56.28	1.091	1.19	123.1	54.82	1.319	5.007	146.2	55.20	1.181	6.095
	3228174	34	114.4	91.56	5.397	30.533	94.4	17.07	0.069	3.087	130.0	124.51	3.995	20.134
	3231163	38	111.6	29.39	0.365	-0.823	103.3	31.28	0.870	3.439	120.1	24.38	0.298	2.011
	3533102	37	140.3	58.57	1.017	0.473	135.1	60.22	1.336	5.185	146.7	56.07	0.757	3.667
	1839196	41	115.5	48.05	1.203	1.207	113.8	46.66	0.826	4.407	114.6	51.72	1.675	6.603
	2235163	32	108.1	39.59	2.409	8.41	113.5	48.20	2.581	12.092	101.0	31.41	1.223	6.456

Table 7.F: Sample moments for 12 hour annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	90	23.35	0.667	0.334	92.8	23.75	0.566	2.814	86.2	22.55	0.961	6.732
	5704055	37	173.8	62.2	0.785	0.003	179.1	64.65	0.704	4.417	165.2	62.00	0.978	3.583
	5806066	41	101.3	27.51	1.227	0.948	103.6	29.16	1.292	5.045	97.9	23.85	1.052	4.925
	5808001	30	96.5	31.86	1.463	1.521	92.2	31.41	1.957	8.003	96.7	34.13	1.126	4.679
	6108001	37	104.2	37.42	1.731	4.699	97.5	23.49	0.600	3.617	110.8	47.56	1.476	5.195
	6206035	41	91.7	25.55	0.043	-0.395	86.6	25.89	0.092	3.231	94.9	26.25	0.106	3.118
	5302001	41	140.8	45.9	1.158	3.114	143.2	53.46	1.216	5.951	132.1	33.89	-0.225	1.936
	5302003	36	114.5	42.57	1.774	4.78	121.5	49.64	1.814	7.398	102.8	30.41	0.512	3.765
	5402001	36	132.6	38.32	0.757	0.349	135.7	33.90	0.591	3.492	125.1	42.74	1.195	4.929
	5402002	36	123	39.51	1.138	1.057	120.0	43.84	1.089	4.084	122.0	35.05	1.574	7.074
	4209093	36	101.4	26.87	0.971	0.743	102.8	31.85	1.045	4.054	102.4	22.68	0.320	2.472
	4311001	37	115.4	25.57	0.36	-0.773	102.7	17.89	0.694	4.356	129.2	25.19	-0.322	3.168
	4409091	41	78.5	15.86	-0.156	0.246	78.5	20.16	0.579	4.634	80.7	14.07	0.172	3.524
	4511111	37	98.7	36.13	1.753	3.627	96.9	40.38	1.696	6.511	98.4	32.17	2.026	10.520
	4708084	37	73.5	18.75	0.739	0.13	72.5	19.02	0.987	3.961	74.3	18.41	0.580	4.292
	4811075	33	84.7	35.35	2.27	6.881	88.5	43.28	2.277	9.356	80.9	24.44	0.801	4.860
	5210069	41	78.4	23.52	1.315	1.329	74.5	20.75	1.099	4.064	84.3	25.46	1.445	6.161

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	97.4	39.76	1.574	1.572	92.8	39.38	1.294	5.030	101.7	39.43	2.314	10.408
	2917001	36	99.9	31.3	0.806	1.126	89.4	30.10	0.906	4.941	108.7	29.47	1.347	5.534
	3117070	41	101.3	18.78	0.052	0.038	97.1	18.00	-0.025	2.925	107.7	19.69	0.033	3.339
	3118102	33	96.6	29.32	1.996	4.32	102.9	38.63	1.537	4.948	93.2	18.74	0.485	4.608
	3411017	41	97.2	34.2	1.189	1.054	97.5	28.87	0.872	4.102	95.7	40.57	1.458	5.286
	3416002	33	103.1	31.2	2.037	6.648	103.1	38.55	2.346	10.803	105.4	24.94	0.414	2.705
	3516022	41	102.1	28.43	0.997	0.158	96.6	17.79	0.253	3.556	109.1	37.14	0.594	2.933
	3613004	41	109.3	42.35	3.177	0.556	99.0	22.98	1.348	5.621	121.2	57.10	2.554	11.820
	3710006	41	83.9	16.56	0.59	0.391	84.9	19.90	0.501	3.104	108.7	29.47	1.347	5.534
	3116003	36	109.9	70.82	3.987	17.636	94.8	21.68	0.584	2.719	126.9	96.31	2.892	12.233
	3116006	34	94.5	21.26	0.291	-0.669	82.1	14.80	0.146	2.653	107.2	18.29	0.015	2.804
	3216001	39	95.9	26.66	1.184	0.617	97.5	27.76	1.149	4.011	94.3	25.10	1.289	5.011
	3217001	39	95.3	19.07	1.278	2.019	92.4	23.38	0.963	5.855	95.8	15.64	0.819	3.554
	3217002	39	95.5	21.9	-0.102	-0.984	98.4	44.50	2.906	14.545	102.5	18.07	-0.504	3.270
	3217003	37	99	23.01	0.352	-0.281	96.2	25.78	0.625	3.620	100.1	19.24	0.262	2.528
	2719001	41	90.2	21.26	0.33	-0.273	84.1	21.34	1.074	6.457	97.1	16.40	0.472	2.571
	2722002	41	77.6	26.6	1.803	3.958	70.7	22.31	2.577	12.301	90.3	28.40	1.371	6.509
	2224038	41	87.6	22.15	0.181	-0.499	83.2	22.76	0.356	2.781	91.2	21.04	0.258	2.324
South West	1437116	41	110.7	37.72	1.569	4.9	103.7	35.08	1.940	9.229	118.7	39.82	1.442	5.862
	1534002	33	101.2	30.6	1.274	2.158	102.3	35.14	1.453	6.345	99.2	26.27	1.004	4.987
	1737001	37	116.5	52.16	1.41	2.392	120.2	58.86	1.662	6.506	110.1	43.95	0.666	2.726
	2025001	37	110.2	36.88	0.701	0.171	114.2	41.82	0.672	3.534	103.7	30.57	0.511	3.457

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	95.2	20.78	0.425	1.01	94.8	19.27	1.141	6.709	96.0	22.71	-0.225	2.307
	3121143	36	84.5	23.81	0.514	0.63	79.4	20.98	-0.262	3.299	88.3	26.00	0.924	3.999
	3519125	39	101.3	75.79	5.465	29.88	86.7	23.46	0.535	3.234	118.5	107.61	4.034	20.321
	3818054	33	85.4	16.56	0.971	1.662	86.0	18.61	1.347	6.063	87.7	16.40	0.405	4.231
	4023001	38	98.7	47.11	3.456	16.006	110.2	58.76	2.890	13.695	85.4	20.44	-0.160	6.345
	2330009	41	104	43.06	1.087	-0.404	94.9	34.49	0.865	3.827	114.2	50.90	0.956	4.027
East	5718002	31	160.7	82.34	1.794	3.723	139.5	46.33	0.515	2.748	175.3	100.77	1.472	5.346
	4734079	41	190.9	134.23	3.507	14.581	172.6	88.13	2.761	13.728	213.1	174.68	3.186	15.478
	4929001	36	188.9	86.13	0.558	-0.217	159.6	74.08	0.568	3.159	212.9	90.70	0.553	3.152
	5331048	39	191.5	81.03	1.314	2.622	191.9	76.42	0.872	4.542	182.6	87.92	1.926	9.195
	5428001	34	180.8	69.23	0.535	-0.043	180.8	73.19	0.837	4.294	180.6	65.29	0.224	3.241
	5428002	34	184.3	71.51	0.506	-0.6	170.3	75.68	0.982	4.083	195.2	65.77	0.268	2.672
	3228174	34	130.8	94.6	4.543	23.194	108.1	33.15	1.867	9.189	147.4	125.78	3.529	17.024
	3231163	38	139.1	47.11	0.689	0.243	134.0	55.88	0.932	3.820	142.3	35.42	0.314	3.114
	3533102	37	187.8	87	0.888	-0.066	186.3	90.24	1.313	4.727	188.8	83.25	0.427	2.375
	1839196	41	143.1	73.79	1.325	0.744	139.2	69.19	0.825	3.188	143.9	81.75	1.818	6.411
	2235163	32	142.9	53.11	2.567	10.177	155.4	65.66	2.720	12.496	128.3	39.59	0.362	4.221

Table 7.G: Sample moments for 1 day annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	108.6	30.79	0.173	-1.002	107.8	25.81	0.186	2.340	108.4	35.76	0.215	2.484
	5704055	37	205.8	74.1	0.582	-0.375	209.6	74.86	0.172	2.604	196.8	77.18	0.964	4.289
	5806066	41	116.2	34.01	1.236	1.582	118.0	32.04	1.007	5.787	114.1	35.74	1.626	7.045
	5808001	30	111.4	37.69	1.408	1.314	102.1	28.79	1.609	7.184	114.9	44.24	1.065	4.029
	6108001	37	117.2	41.94	2.282	7.172	107.1	20.13	0.821	3.491	127.4	55.38	1.661	6.106
	6206035	41	108.7	34.01	0.575	0.795	100.8	30.29	0.312	2.669	114.6	39.34	0.585	3.256
	5302001	41	161.3	53.06	1.048	1.975	164.0	62.17	1.071	4.617	150.0	40.03	-0.314	2.059
	5302003	36	136	51.4	1.468	2.47	144.1	57.77	1.573	5.742	122.2	40.68	0.878	3.929
	5402001	36	160.3	56.11	1.064	1.221	158.1	47.98	0.770	2.902	156.6	65.30	1.294	5.587
	5402002	36	145.9	59.56	1.295	1.759	138.3	56.66	1.085	3.857	148.9	62.68	1.669	7.246
	4209093	36	109.8	25.33	0.71	0.402	110.3	29.07	1.043	4.024	111.2	22.19	-0.297	2.854
	4311001	37	126.4	32.41	1.148	1.984	109.7	17.24	0.072	4.677	145.3	34.18	0.792	5.158
	4409091	41	91.2	20.67	1.186	3.162	93.8	25.51	0.980	4.903	89.5	13.51	0.216	3.315
	4511111	37	111.4	38.53	1.917	4.798	109.5	36.28	1.605	6.479	110.8	42.47	2.165	10.763
	4708084	37	80.3	18.44	0.886	0.055	80.0	20.44	0.982	3.545	80.2	16.08	0.879	4.552
	4811075	33	91.4	35.64	1.892	4.911	96.3	43.78	1.821	7.209	86.3	23.77	0.569	4.150
	5210069	41	85.6	22.58	1.044	0.884	82.5	21.34	0.763	3.548	90.9	23.97	1.266	5.557

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	110.9	42.64	1.918	5.869	110.7	45.21	1.986	8.537	109.4	37.69	2.143	9.932
	2917001	36	112.8	31.44	0.824	1.53	104.5	30.28	0.771	5.455	122.9	29.87	1.175	5.503
	3117070	41	116.2	23.46	1.146	1.914	111.5	21.79	1.231	6.585	122.0	25.60	0.861	5.878
	3118102	33	110.1	35.07	2.218	5.694	118.6	46.66	1.590	5.704	105.1	20.63	0.926	4.259
	3411017	41	102.5	34.43	0.893	0.42	102.3	30.26	0.626	3.251	101.4	39.83	1.163	4.662
	3416002	33	117.4	28.71	2.17	6.9	117.7	36.44	2.264	9.954	118.6	20.64	0.596	2.633
	3516022	41	116.1	30.51	0.718	-1.024	111.5	23.24	0.441	2.914	122.6	37.29	0.463	3.348
	3613004	41	122.1	64.58	4.695	1.602	108.7	24.20	1.523	7.082	137.9	92.59	3.437	16.785
	3710006	41	92.8	18.17	0.311	-0.513	96.4	19.74	-0.165	3.074	122.9	29.87	1.175	5.503
	3116003	36	133.2	122.56	5.052	27.677	107.0	31.20	1.851	7.913	161.5	167.94	3.734	18.260
	3116006	34	109.3	29.91	1.082	1.684	95.7	23.42	1.218	5.042	123.5	28.40	1.333	6.460
	3216001	39	106.5	28.64	1.396	1.688	109.6	30.25	1.050	4.386	102.5	25.87	2.244	9.303
	3217001	39	106.9	20.55	0.379	-0.353	102.3	25.17	0.193	4.089	108.8	17.96	-0.124	2.218
	3217002	39	106	23.23	0.23	-0.373	109.6	43.76	2.504	12.129	111.3	18.41	0.361	3.927
	3217003	37	115.1	35.91	1.416	3.987	115.7	44.78	1.360	6.151	111.7	20.68	-0.054	2.648
	2719001	41	104.7	25.66	1.021	2.55	100.5	24.42	0.167	3.281	105.9	17.79	0.317	2.447
	2722002	41	92.2	30.83	0.837	-0.287	87.5	29.58	0.872	3.655	102.8	29.78	0.901	3.700
	2224038	41	96.4	25.13	0.642	-0.66	89.8	22.52	0.534	2.549	103.7	27.04	0.578	3.524
South West	1437116	41	135.4	56.44	2.313	7.836	127.2	47.47	2.756	13.716	144.0	66.18	2.030	7.230
	1534002	33	127	42.13	1.134	0.97	128.5	46.45	1.501	5.472	124.4	38.17	0.726	3.735
	1737001	37	133	58.97	1.109	0.828	137.4	63.00	1.387	5.112	124.8	55.07	0.747	2.708
	2025001	37	116.2	35.61	0.819	-0.063	119.0	40.18	0.835	3.333	110.8	30.65	0.617	3.348

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	116.4	30.22	1.064	0.458	117.9	31.29	1.262	4.141	113.6	28.72	0.882	4.192
	3121143	36	92.8	24.26	0.613	0.042	89.7	18.98	0.068	3.646	95.7	28.22	0.672	3.136
	3519125	39	111.1	75.41	5.182	27.615	96.1	29.19	1.009	4.119	128.3	105.26	4.011	20.221
	3818054	33	93.9	18.15	0.559	-0.148	94.4	20.16	0.523	3.717	96.2	16.82	0.487	3.120
	4023001	38	110.5	48.26	2.73	11.145	121.9	58.48	2.499	11.461	98.4	27.48	-0.461	3.222
	2330009	41	126.7	62.41	1.259	-0.377	112.9	45.71	0.655	3.436	143.0	76.59	1.083	4.394
East	5718002	31	210.7	93.79	0.755	-0.112	201.1	75.18	0.259	3.339	213.2	108.87	0.850	3.146
	4734079	41	239.8	142.21	2.585	9.699	222.4	112.23	2.178	10.237	258.4	171.17	2.674	12.662
	4929001	36	251.4	122.91	0.57	-0.563	224.9	117.55	0.867	3.657	270.3	124.60	0.523	2.944
	5331048	39	254.6	111.02	1.161	1.505	260.7	109.82	1.035	4.898	232.5	115.54	1.537	7.136
	5428001	34	240.3	89.37	0.386	-0.372	248.7	93.14	0.719	3.911	229.3	85.50	0.082	2.368
	5428002	34	250	88.27	0.034	-0.888	242.1	100.32	0.309	2.917	252.2	78.36	-0.192	2.113
	3228174	34	155.9	110.87	3.79	16.621	135.3	56.02	1.498	7.214	167.6	144.56	3.203	14.402
	3231163	38	175.7	69.55	1.336	1.562	176.3	75.00	1.242	5.138	170.8	65.00	1.613	6.613
	3533102	37	232.6	108.18	0.833	0.203	226.1	106.25	1.445	5.900	239.6	109.85	0.308	2.505
	1839196	41	174.4	92.94	1.534	1.208	168.0	89.82	1.335	4.598	177.6	99.36	1.858	6.752
	2235163	32	188.9	71.41	1.811	4.854	204.3	86.47	1.940	7.598	169.9	57.23	0.350	4.516

Table 7.H: Sample moments for 3 day annual maximum rainfall

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
North West	6401002	37	148.1	43.81	0.499	-0.36	149.9	41.73	0.716	3.356	144.8	46.20	0.475	3.057
	5704055	37	302.3	109.55	0.887	1.502	286.5	94.21	0.177	2.568	308.7	123.25	1.106	5.508
	5806066	41	168.1	56.21	1.233	1.079	164.6	45.04	1.212	5.288	175.9	68.24	0.974	4.177
	5808001	30	164.5	45.09	0.77	0.214	155.6	38.70	0.203	2.384	167.0	51.37	0.777	3.740
	6108001	37	159.2	50.47	1.661	3.599	145.5	38.63	1.172	4.157	172.7	58.04	1.672	6.445
	6206035	41	153.1	48.27	0.827	1.035	138.1	42.34	1.128	5.782	168.4	52.19	0.494	3.056
	5302001	41	232.6	75.25	0.754	0.03	228.1	76.92	0.678	2.959	229.2	76.46	1.014	5.099
	5302003	36	192.4	76.92	0.849	-0.201	197.4	73.32	0.942	3.339	178.4	81.52	1.070	4.047
	5402001	36	220.2	78.81	0.85	0.161	217.6	72.60	1.005	3.651	213.1	88.80	0.840	4.039
	5402002	36	206.4	85.99	1.139	0.966	196.4	78.14	1.021	3.889	208.7	95.21	1.297	5.143
	4209093	36	146.4	26.58	0.296	0.08	146.1	32.20	0.324	3.272	147.9	19.61	0.050	2.462
	4311001	37	185.4	56.32	2.103	7.365	162.9	32.92	-0.062	4.351	208.5	66.02	2.102	9.308
	4409091	41	125	24.16	-0.014	-0.462	123.2	25.24	0.095	3.388	128.9	23.32	-0.087	2.743
	4511111	37	150.1	39.08	0.708	0.882	147.2	38.97	0.683	3.078	150.6	40.90	0.810	6.158
	4708084	37	111.8	23.85	0.153	-0.474	109.1	26.02	0.197	3.251	114.0	21.17	0.441	2.392
	4811075	33	128.5	43.4	1.235	1.683	131.2	45.96	1.004	3.943	124.3	39.57	1.835	9.803
	5210069	41	117.8	31.41	1.377	4.707	111.4	27.57	0.716	3.983	127.8	36.10	1.518	8.204

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Central West	4010001	41	152.3	50.68	1.49	1.923	150.5	47.54	1.578	6.660	153.0	53.83	1.624	6.884
	2917001	36	155	42.8	0.551	0.575	142.6	41.27	0.519	3.870	165.7	41.23	0.938	4.885
	3117070	41	154.8	33.91	0.707	-0.348	146.5	29.57	0.488	4.020	162.5	39.20	0.520	2.814
	3118102	33	151.2	45.54	2.337	8.436	167.0	55.84	2.142	9.525	141.7	34.80	0.948	4.877
	3411017	41	128.3	36.22	0.51	-0.359S	132.7	35.40	0.341	3.003	119.6	37.84	0.902	3.880
	3416002	33	166.8	37.12	0.936	0.482	154.3	33.76	1.917	8.979	176.8	36.84	0.563	3.394
	3516022	41	156.1	37.2	1.09	0.157	151.0	34.70	1.076	3.993	163.5	39.25	1.121	6.520
	3613004	41	174.3	72.34	4.513	-0.796	161.7	32.06	0.254	2.165	189.8	102.35	3.543	17.448
	3710006	41	122.1	29.36	1.003	0.96	123.9	28.51	0.797	3.285	165.7	41.23	0.938	4.885
	3116003	36	177.2	135.63	4.857	26.365	142.4	42.63	1.741	7.342	214.3	181.72	3.742	18.484
	3116006	34	150.3	36.03	0.334	-0.799	131.6	27.04	0.323	2.585	168.6	32.78	0.168	2.397
	3216001	39	146.0	32.96	1.096	1.349	148.6	32.79	1.165	5.386	142.7	32.87	1.183	5.392
	3217001	39	150.7	27.05	1.198	2.768	145.5	35.45	0.247	6.312	150.4	23.86	0.717	3.724
	3217002	39	150.5	34.04	-0.036	-0.522	155.9	69.90	2.890	14.387	159.3	27.26	-0.408	3.534
	3217003	37	165.2	46.12	0.857	1.607	165.4	58.41	0.790	3.728	160.4	25.70	-0.057	2.538
	2719001	41	140.7	30.78	0.59	0.287	135.2	31.27	0.496	3.375	148.6	25.68	1.149	4.185
	2722002	41	119.9	39.31	0.64	-0.355	119.7	44.49	0.862	3.594	125.3	29.57	0.149	2.613
	2224038	41	130.8	42.27	1.875	6.856	122.5	31.71	1.997	8.920	138.6	52.45	1.566	5.666
South West	1437116	41	180.9	76.74	2.634	12.7	159.3	53.06	1.527	6.645	209.1	92.48	2.694	11.693
	1534002	33	169.5	51.72	0.943	0.442	170.3	56.79	0.818	3.464	165.8	48.43	1.241	5.781
	1737001	37	183.9	66.86	0.674	0.469	199.4	67.17	0.873	4.162	161.0	64.96	0.559	2.730
	2025001	37	155.6	42.96	0.385	-0.64	155.3	48.17	0.479	3.002	152.4	39.42	0.161	2.613

Region	Station ID	Record Length (Year)	Full Series Data				First Sub-series Data				Second Sub-series Data			
			Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis	Mean (mm)	Std. Dev. (mm)	Skewness	Kurtosis
Inland	4819027	40	162	50.23	2.341	5.939	170.1	59.73	2.054	8.238	149.8	29.92	1.541	6.631
	3121143	36	123.8	39.32	0.505	-0.058	123.8	31.78	-0.096	2.988	121.1	46.15	0.881	3.669
	3519125	39	148.4	73.29	4.449	22.592	136.3	41.77	1.255	5.250	161.6	97.59	4.008	20.201
	3818054	33	130.2	24.63	0.365	-0.243	134.9	23.12	0.968	5.210	127.7	24.75	0.121	2.497
	4023001	38	146.6	85.5	4.34	21.602	168.0	107.97	3.567	17.883	122.2	31.76	0.409	4.896
	2330009	41	180.1	110.08	1.871	4.89	169.8	103.56	2.145	9.477	189.6	118.80	1.780	7.551
East	5718002	31	328.9	140.72	0.528	-0.341	334.7	140.81	0.560	3.699	317.3	143.09	0.662	3.466
	4734079	41	353.6	181.91	1.648	3.117	351.0	179.85	1.652	6.379	356.4	180.05	1.891	8.309
	4929001	36	404.7	206.34	0.774	-0.369	372.9	209.47	1.266	4.322	427.1	196.41	0.505	3.022
	5331048	39	383	180.89	1.471	3.772	396.6	202.18	1.704	7.957	343.9	151.91	0.465	2.905
	5428001	34	396.6	157.72	0.872	1.163	423.1	172.91	1.209	5.075	364.2	139.14	0.245	3.168
	5428002	34	412.4	153.94	0.788	0.553	429.2	184.11	0.808	3.727	385.8	123.53	0.159	2.681
	3228174	34	198.7	119.4	3.035	9.955	175.4	56.36	0.999	4.582	213.0	156.63	2.455	9.057
	3231163	38	268.9	111.43	1.185	0.849	264.9	111.53	0.648	2.927	265.5	116.51	1.821	7.134
	3533102	37	346	165.59	0.575	-0.596	326.6	151.97	1.212	4.972	362.8	178.73	0.161	2.195
	1839196	41	248	119.05	0.891	-0.061	243.2	121.74	0.955	3.818	246.8	119.87	0.927	3.931
	2235163	32	265.4	109.17	1.363	1.869	295.9	109.72	0.962	3.492	230.8	106.28	2.015	10.324

APPENDIX 8: L-SKEWNESS AND L-KURTOSIS OF ANNUAL MAXIMUM RAINFALL SERIES

Table 8.A: L-Skewness and L-Kurtosis for northwest region (short duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Kedah	5806066	15 min	0.072	0.0926	0.089	0.114
		30 min	0.096		0.042	
		1 hr	0.197		0.083	
		3 hrs	0.079		0.021	
	5808001	15 min	0.075		0.307	
		30 min	0.096		0.098	
		1 hr	-0.048		0.090	
		3 hrs	0.219		0.279	
Pinang	5302001	15 min	0.082		0.223	
		30 min	-0.137		0.116	
		1 hr	0.000		0.040	
		3 hrs	0.177		0.081	
	5402002	15 min	0.256		0.243	
		30 min	0.094		0.148	
		1 hr	0.037		0.185	
		3 hrs	0.116		0.171	
Perak	4209093	15 min	-0.011		0.042	
		30 min	0.157		0.183	
		1 hr	0.244		0.069	
		3 hrs	0.192		0.102	
	4409091	15 min	-0.026		0.160	
		30 min	-0.020		0.067	
		1 hr	-0.016		-0.053	
		3 hrs	0.037		0.157	
	4708084	15 min	0.132		0.233	
		30 min	0.034		0.129	
		1 hr	0.146		0.071	
		3 hrs	0.088		0.084	
	4811075	15 min	0.151		0.055	
		30 min	0.148		0.036	
		1 hr	-0.033		0.078	
		3 hrs	0.117		0.277	
	5210069	15 min	0.075		0.063	
		30 min	0.204		0.082	
		1 hr	0.277		0.018	
		3 hrs	0.028		0.035	

Table 8.B: L-Skewness and L-Kurtosis for northwest region (long duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Perlis	6401002	6 hr	0.224	0.162	0.259	0.189
		12 hr	0.084		0.293	
		1 day	0.068		0.009	
		3 day	0.145		0.114	
Kedah	5704055	6 hr	0.151		0.084	
		12 hr	0.285		0.094	
		1 day	0.208		0.172	
		3 day	0.176		0.150	
	5808001	6 hr	0.286		0.344	
		12 hr	0.272		0.207	
		1 day	0.288		0.184	
		3 day	0.172		0.113	
Pinang	5302003	6 hr	0.036		0.077	
		12 hr	0.105		0.160	
		1 day	0.209		0.113	
		3 day	0.295		0.114	
	5402001	6 hr	0.348		0.255	
		12 hr	0.249		0.223	
		1 day	0.221		0.243	
		3 day	0.181		0.130	
Perak	4311001	6 hr	0.087		0.323	
		12 hr	-0.058		0.096	
		1 day	0.123		0.237	
		3 day	0.376		0.329	
	4409091	6 hr	0.009		0.179	
		12 hr	-0.007		0.128	
		1 day	0.051		0.165	
		3 day	-0.015		0.048	
	4511111	6 hr	0.259		0.424	
		12 hr	0.190		0.368	
		1 day	0.227		0.383	
		3 day	0.100		0.283	
	4708084	6 hr	0.096		0.128	
		12 hr	0.082		0.172	
		1 day	0.162		0.235	
		3 day	0.138		-0.035	

Table 8.C: L-Skewness and L-Kurtosis for central west region (short duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Selangor	2917001	15 min	0.064	0.119	0.258	0.171
		30 min	0.110		0.312	
		1 hr	0.164		0.088	
		3 hrs	0.042		0.131	
	3118102	15 min	0.514		0.304	
		30 min	0.134		0.013	
		1 hr	-0.019		0.011	
		3 hrs	0.002		0.271	
	3411017	15 min	0.377		0.436	
		30 min	0.268		0.262	
		1 hr	0.297		0.241	
		3 hrs	0.302		0.248	
	3516022	15 min	0.168		0.220	
		30 min	-0.075		0.010	
		1 hr	-0.006		0.008	
		3 hrs	0.111		0.145	
	3613004	15 min	-0.032		0.150	
		30 min	0.237		0.287	
		1 hr	0.219		0.157	
		3 hrs	-0.015		0.084	
	3710006	15 min	0.064		0.258	
		30 min	0.110		0.312	
		1 hr	0.164		0.088	
		3 hrs	0.042		0.131	
Kuala Lumpur	3116003	15 min	0.048		0.241	
		30 min	0.078		0.200	
		1 hr	0.124		0.182	
		3 hrs	0.166		0.268	
	3217003	15 min	-0.092		0.022	
		30 min	-0.019		0.294	
		1 hr	0.066		0.206	
		3 hrs	0.036		0.119	
Negeri Sembilan	2719001	15 min	0.129		0.096	
		30 min	0.033		0.190	
		1 hr	0.172		0.161	
		3 hrs	0.143		0.074	
Melaka	2224038	15 min	-0.042		0.101	
		30 min	0.193		0.039	
		1 hr	0.243		0.147	
		3 hrs	0.249		0.062	

Table 8.D: L-Skewness and L-Kurtosis for central west region (long duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Selangor	2917001	6 hr	0.177	0.137	0.125	0.134
		12 hr	0.260		0.234	
		1 day	0.201		0.329	
		3 day	0.172		0.224	
	3117070	6 hr	0.090		0.088	
		12 hr	-0.002		0.152	
		1 day	0.078		0.234	
		3 day	0.144		0.052	
	3118102	6 hr	0.145		0.334	
		12 hr	0.124		0.204	
		1 day	0.210		0.095	
		3 day	0.164		0.144	
	3411017	6 hr	0.343		0.256	
		12 hr	0.361		0.273	
		1 day	0.278		0.219	
		3 day	0.211		0.144	
	3416002	6 hr	0.121		0.059	
		12 hr	0.135		0.033	
		1 day	0.179		0.005	
		3 day	0.126		0.083	
	3710006	6 hr	0.177		0.125	
		12 hr	0.260		0.234	
		1 day	0.201		0.329	
		3 day	0.172		0.224	
Kuala Lumpur	3217001	6 hr	0.190		0.107	
		12 hr	0.209		0.084	
		1 day	-0.046		-0.061	
		3 day	0.160		0.092	
	3217002	6 hr	-0.058		0.022	
		12 hr	-0.117		0.098	
		1 day	0.044		0.207	
		3 day	-0.097		0.154	
	3217003	6 hr	0.009		0.091	
		12 hr	0.069		0.010	
		1 day	-0.008		0.051	
		3 day	-0.012		0.015	
Negeri Sembilan	2719001	6 hr	0.254		0.131	
		12 hr	0.147		-0.010	
		1 day	0.100		-0.002	
		3 day	0.291		0.174	

Table 8.E: L-Skewness and L-Kurtosis for southwest region (short duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Johor	1437116	15 min	-0.043	0.017	-0.040	0.105
		30 min	-0.050		-0.018	
		1 hr	0.047		0.142	
		3 hrs	0.217		0.195	
	1534002	15 min	0.062		0.210	
		30 min	-0.188		0.022	
		1 hr	-0.051		0.165	
		3 hrs	0.1429		0.162	

Table 8.F: L-Skewness and L-Kurtosis for southwest region (long duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Johor	1534002	6 hr	0.240	0.154	0.147	0.139
		12 hr	0.182		0.150	
		1 day	0.167		0.080	
		3 day	0.229		0.277	
	2025001	6 hr	0.119		0.206	
		12 hr	0.112		0.128	
		1 day	0.150		0.122	
		3 day	0.033		0.004	

Table 8.G: L-Skewness and L-Kurtosis for inland region (short duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Kelantan	4819027	15 min	0.344	0.180	0.365	0.194
		30 min	-0.071		0.146	
		1 hr	0.015		0.018	
		3 hrs	0.025		0.081	
Johor	2330009	15 min	0.409		0.463	
		30 min	0.260		0.219	
		1 hr	0.250		0.143	
		3 hrs	0.158		0.081	
Pahang	3121143	15 min	0.357		0.316	
		30 min	0.086		0.111	
		1 hr	0.156		0.170	
		3 hrs	0.169		0.213	

Table 8.H: L-Skewness and L-Kurtosis for inland region (long duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Johor	2330009	6 hr	0.127	0.181	-0.025	0.123
		12 hr	0.249		0.050	
		1 day	0.272		0.073	
		3 day	0.367		0.140	
Pahang	3818054	6 hr	0.105		0.183	
		12 hr	0.060		0.232	
		1 day	0.121		0.130	
		3 day	0.038		-0.019	
	3121143	6 hr	0.207		0.203	
		12 hr	0.206		0.214	
		1 day	0.193		0.133	
		3 day	0.225		0.161	

Table 8.I: L-Skewness and L-Kurtosis for east coast region (short duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Terengganu	5428001	15 min	0.005	0.147	0.235	0.164
		30 min	-0.081		0.197	
		1 hr	0.203		0.124	
		3 hrs	0.223		0.168	
	5428002	15 min	0.069		0.044	
		30 min	-0.032		0.095	
		1 hr	0.187		0.061	
		3 hrs	0.286		0.313	
Pahang	3231163	15 min	0.069		0.034	
		30 min	0.039		0.133	
		1 hr	0.134		0.060	
		3 hrs	0.147		0.182	
Johor	1839196	15 min	0.122		0.145	
		30 min	0.053		0.304	
		1 hr	0.249		0.168	
		3 hrs	0.228		0.226	
	2235163	15 min	0.306		0.231	
		30 min	0.174		0.152	
		1 hr	0.363		0.207	
		3 hrs	0.204		0.196	

Table 8.J: L-Skewness and L-Kurtosis for east coast region (long duration annual maximum rainfall)

State	Station	Duration	L-Skewness	Regional Average L-Skewness	L-Kurtosis	Regional Average L-Kurtosis
Terengganu	4929001	6 hr	0.069	0.121	0.002	0.121
		12 hr	0.145		0.018	
		1 day	0.149		0.001	
		3 day	0.136		0.071	
	5331048	6 hr	0.305		0.258	
		12 hr	0.252		0.224	
		1 day	0.241		0.202	
		3 day	0.123		0.039	
	5428001	6 hr	0.169		0.145	
		12 hr	0.056		0.129	
		1 day	0.034		-0.018	
		3 day	0.061		0.087	
	5428002	6 hr	0.177		0.242	
		12 hr	0.068		0.015	
		1 day	-0.053		-0.071	
		3 day	0.044		0.048	
Johor	2235163	6 hr	0.154		0.201	
		12 hr	0.028		0.193	
		1 day	0.058		0.267	
		3 day	0.200		0.373	

APPENDIX 9: MANN-KENDALL TREND TEST RESULTS

Table 9.A: Significance of trend in annual rainfall for northwest region

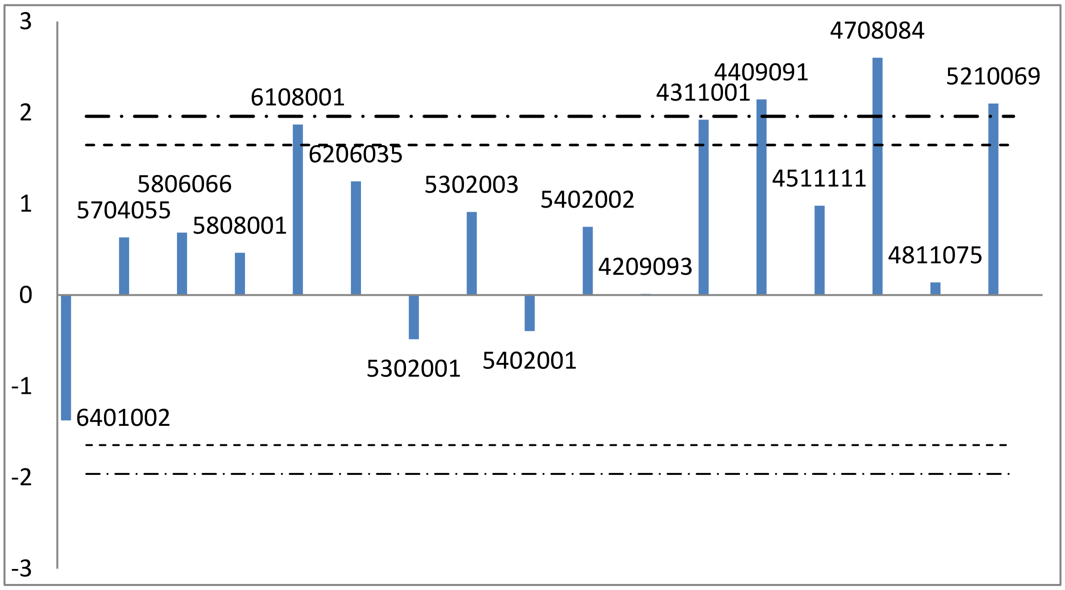

Table 9.B: Significance of trend in annual rainfall for central west region

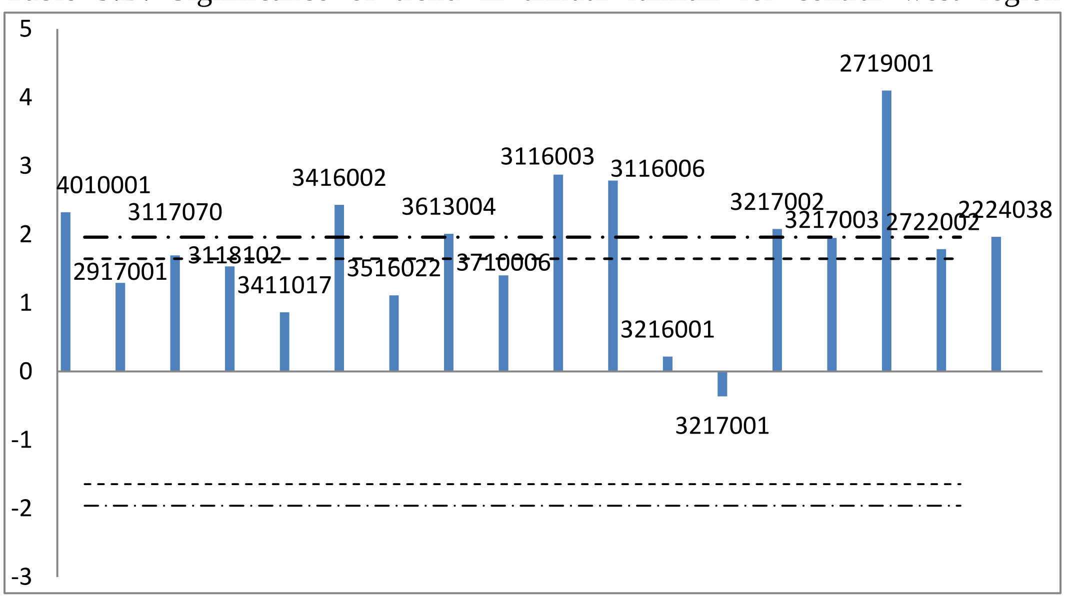

Table 9.C: Significance of trend in annual rainfall for southwest region

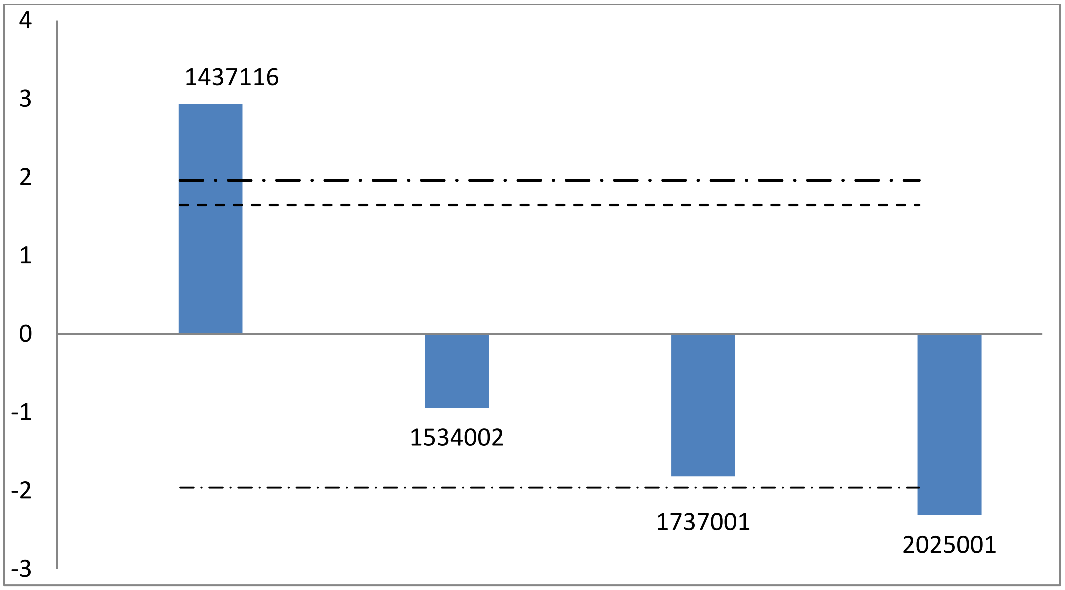

Table 9.D: Significance of trend in annual rainfall for inland region

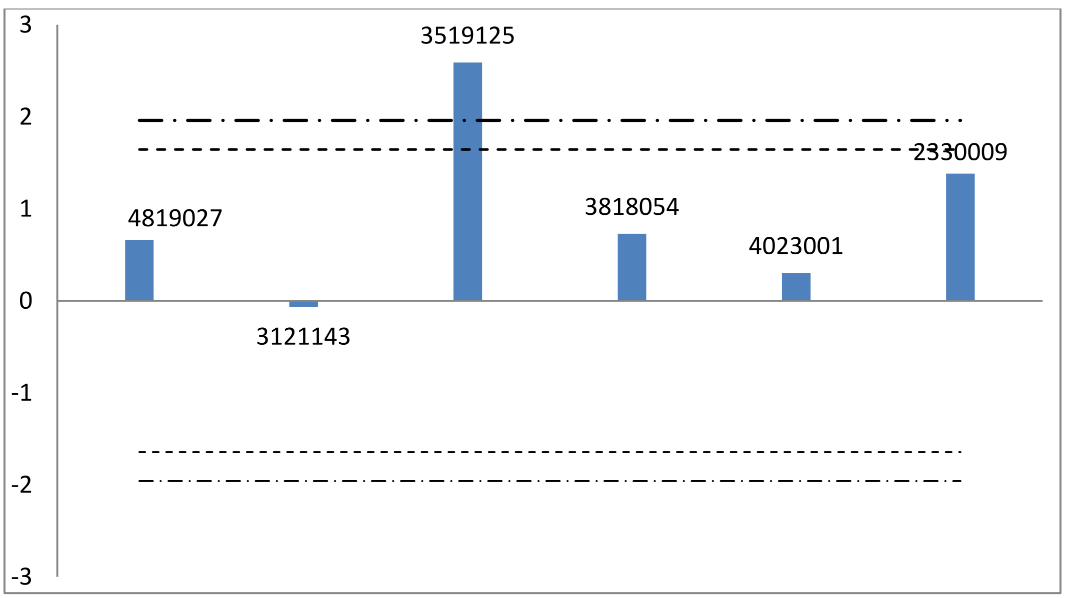

Table 9.E: Significance of trend in annual rainfall for east coast region

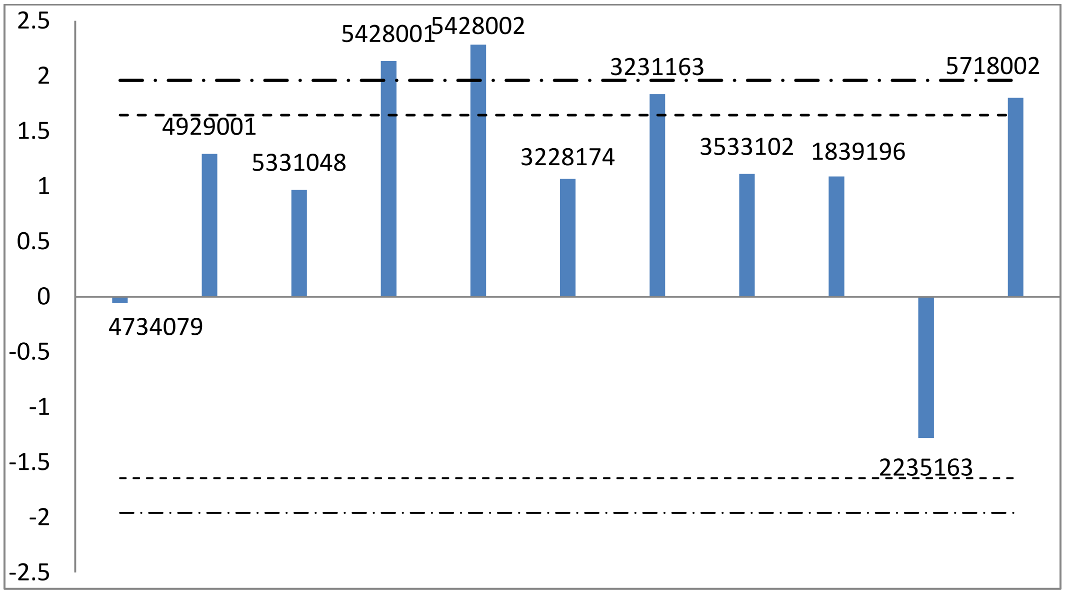

Table 9.F: Significance of trend in seasonal rainfall for northwest region

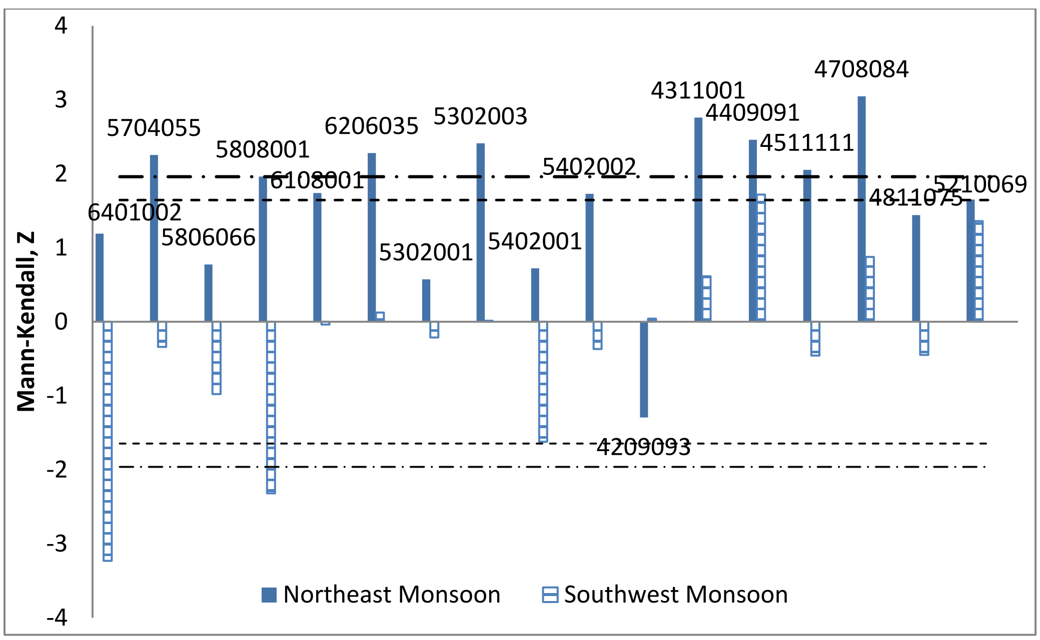

Table 9.G: Significance of trend in seasonal rainfall for central west region

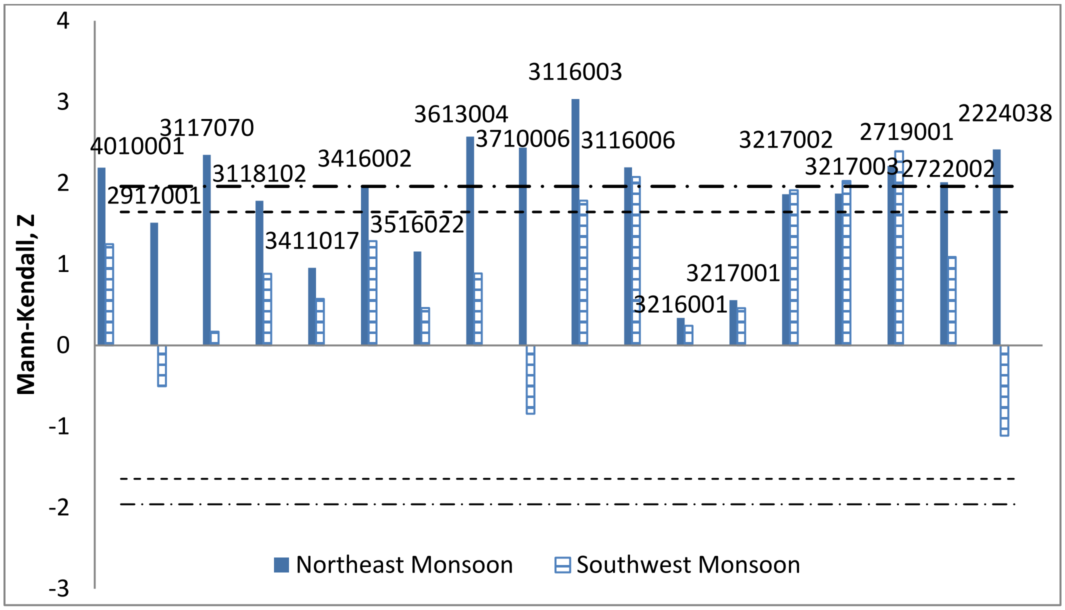

Table 9.H: Significance of trend in seasonal rainfall for southwest region

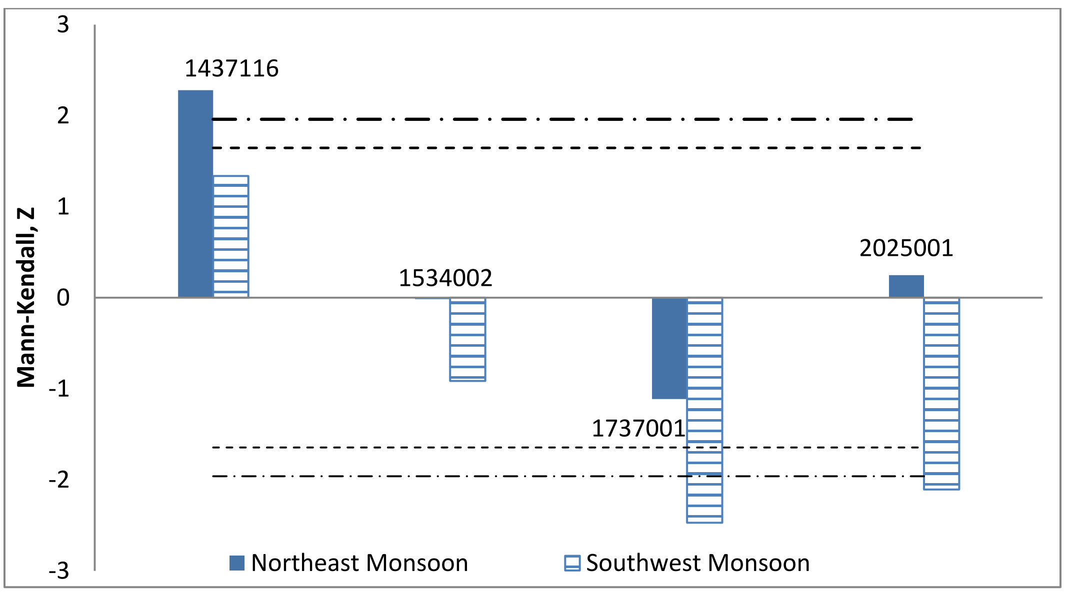

Table 9.I: Significance of trend in seasonal rainfall for inland region

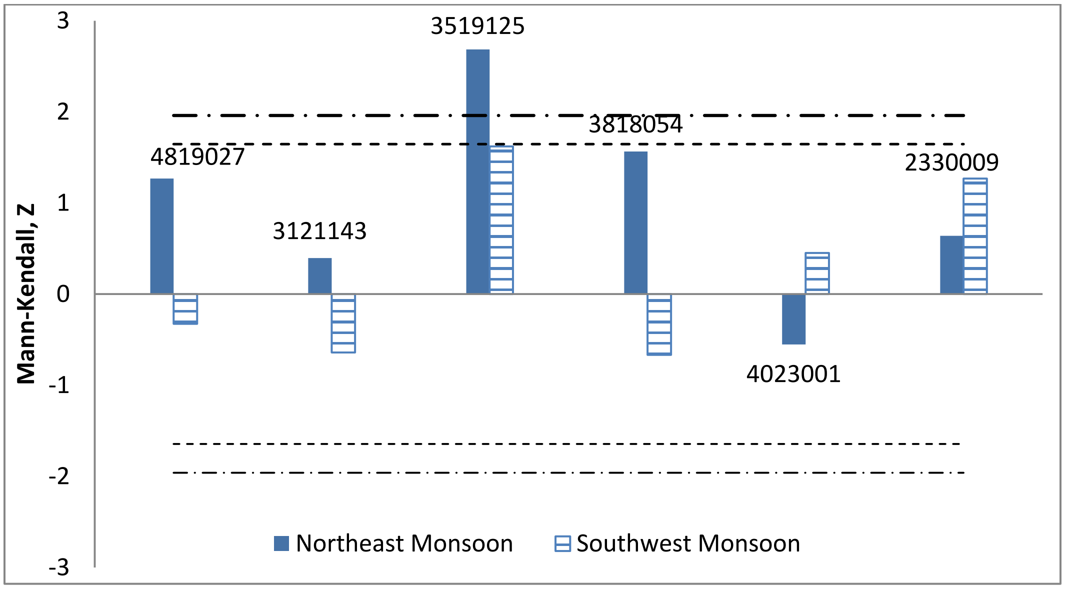

Table 9.J: Significance of trend in seasonal rainfall for east coast region

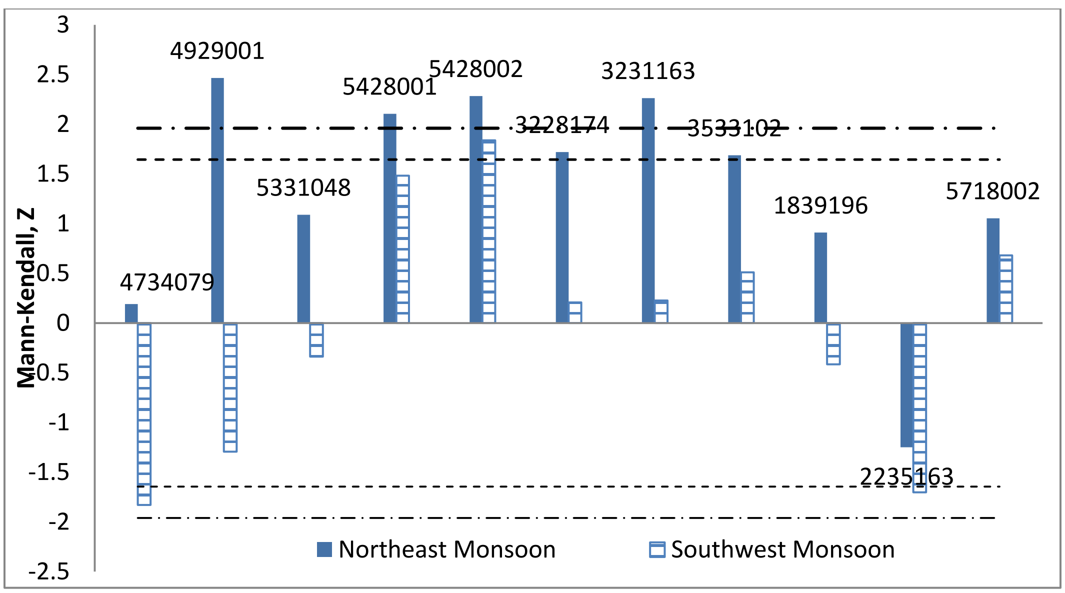

Table 9.K: Significance of trend in inter-monsoon rainfall for northwest region

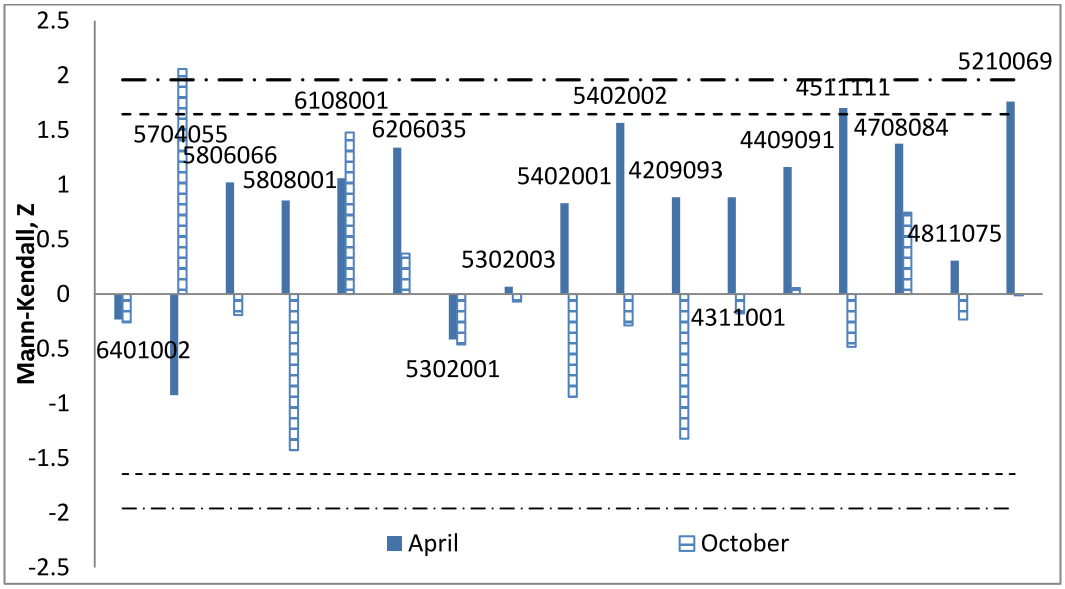

Table 9.L: Significance of trend in inter-monsoon rainfall for central west region

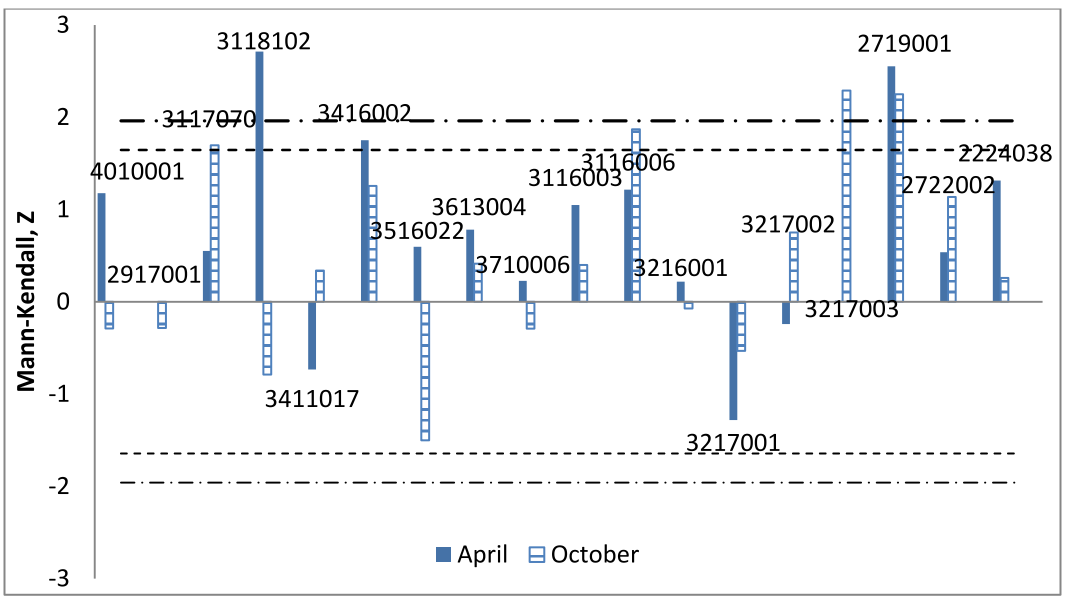

Table 9.M: Significance of trend in inter-monsoon rainfall for southwest region

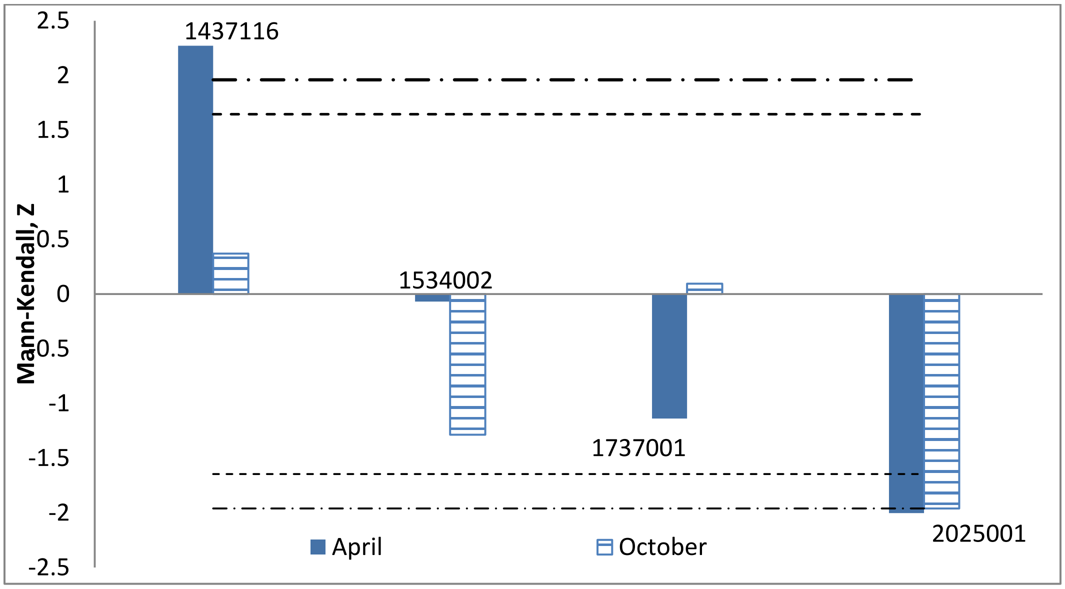

Table 9.N: Significance of trend in inter-monsoon rainfall for inland region

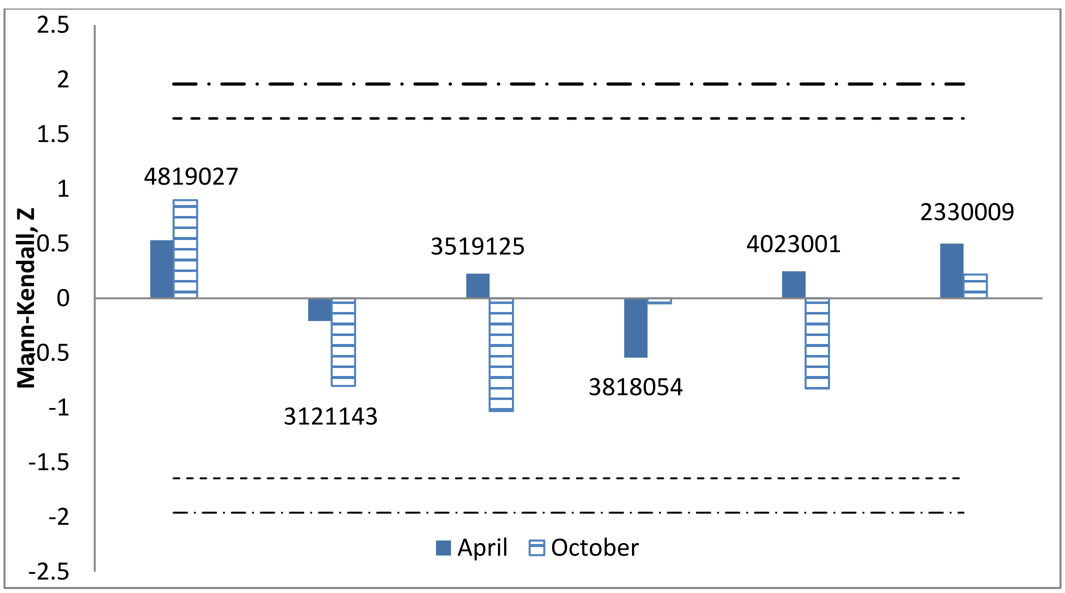

Table 9.O: Significance of trend in inter-monsoon rainfall for east coast region

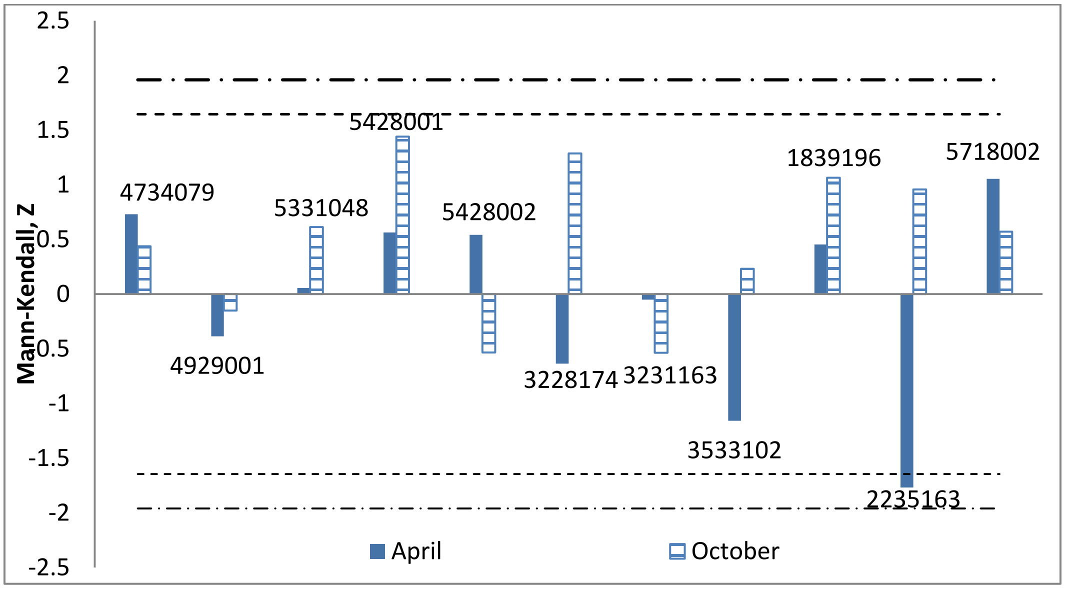

Table 9.P: Significance of trend in short-duration annual maximum rainfall for northwest region

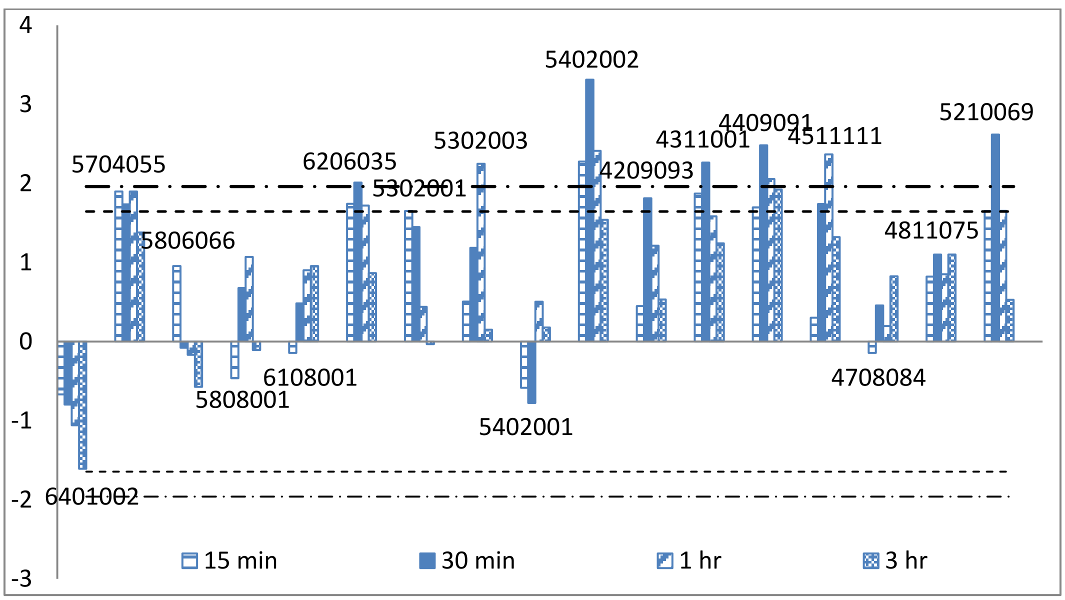

Table 9.Q: Significance of trend in long-duration annual maximum rainfall for northwest region

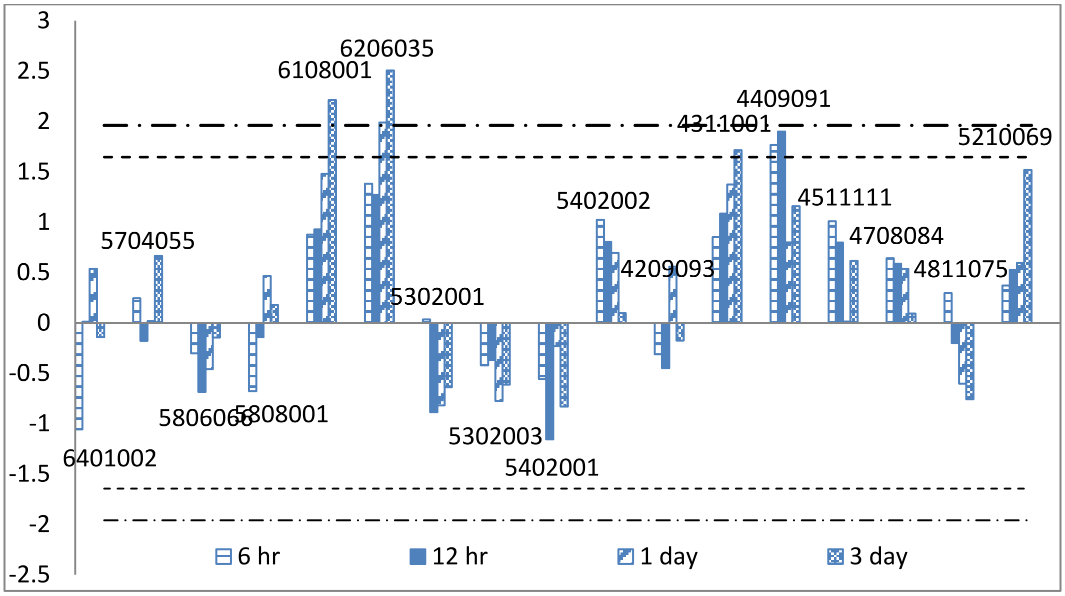

Table 9.R: Significance of trend in short-duration annual maximum rainfall for central west region

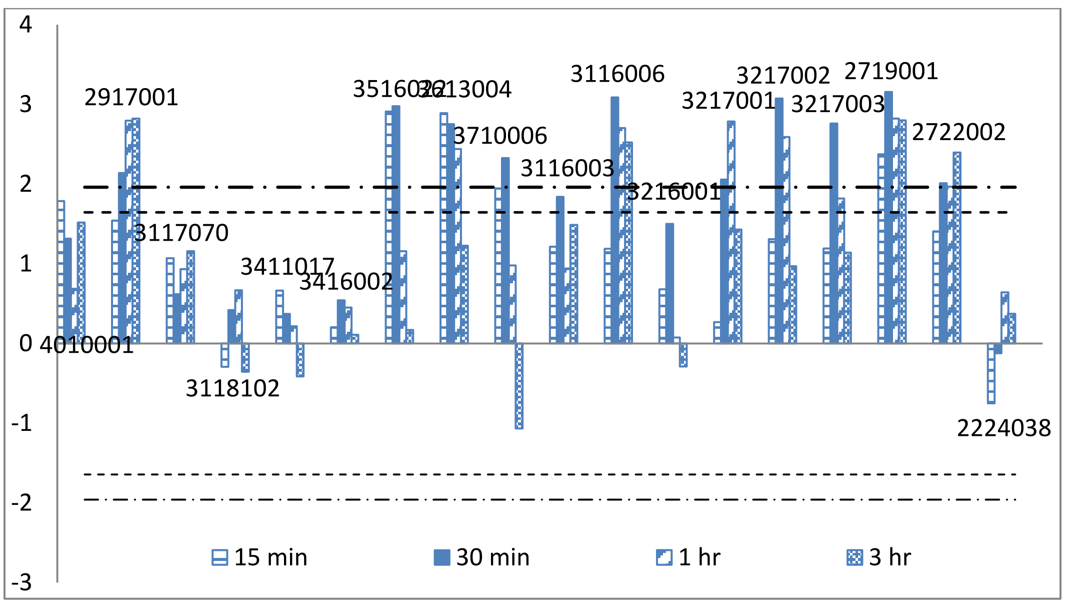

Table 9.S: Significance of trend in long-duration annual maximum rainfall for central west region

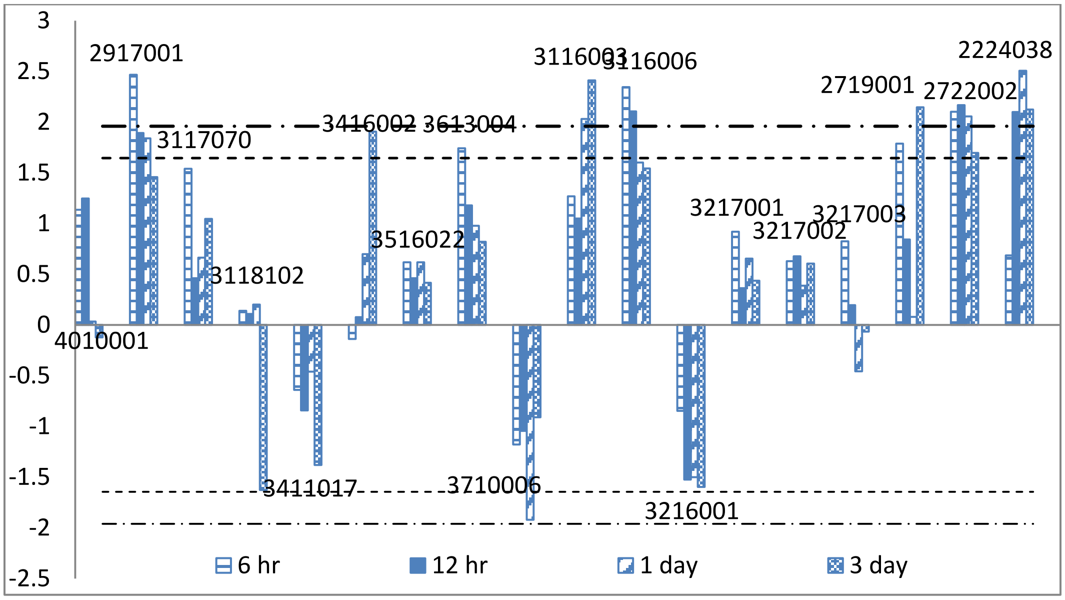

Table 9.T: Significance of trend in short-duration annual maximum rainfall for south west region

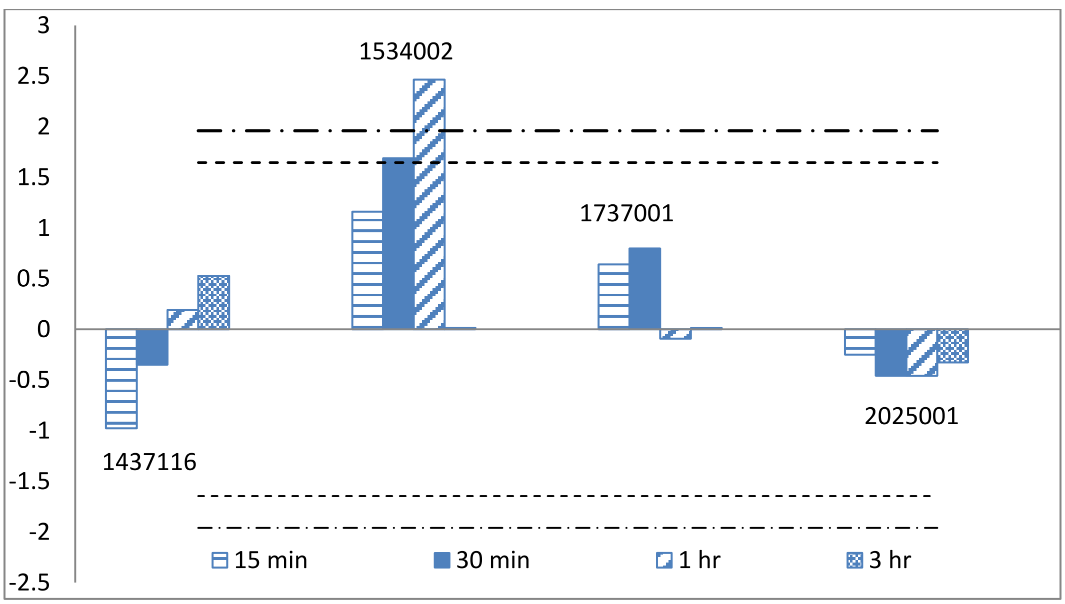

Table 9.U: Significance of trend in long-duration annual maximum rainfall for south west region

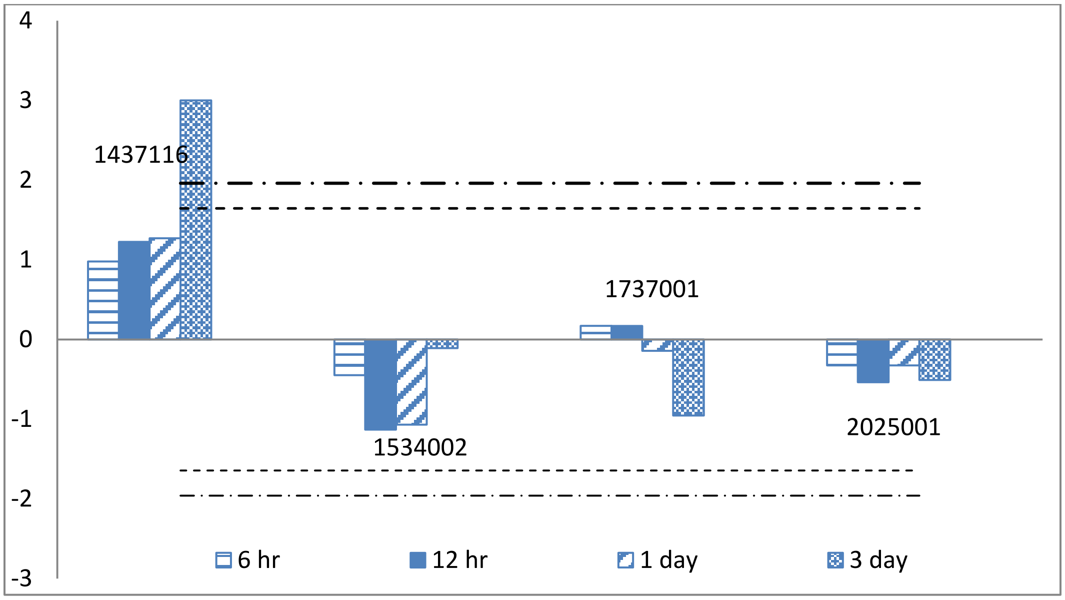

Table 9.V: Significance of trend in short-duration annual maximum rainfall for inland region

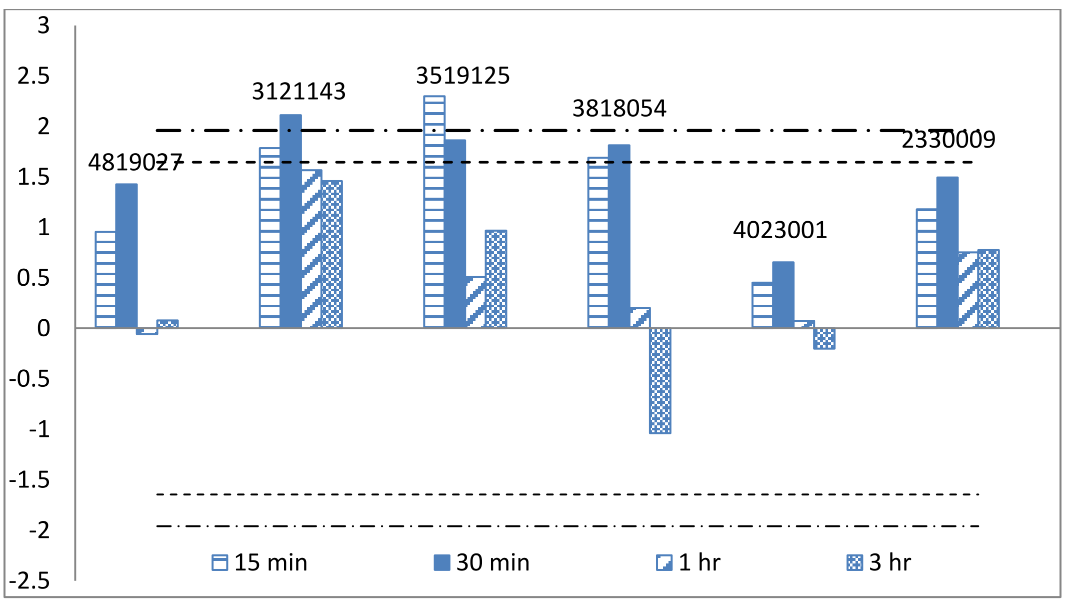

Table 9.W: Significance of trend in long-duration annual maximum rainfall for inland region

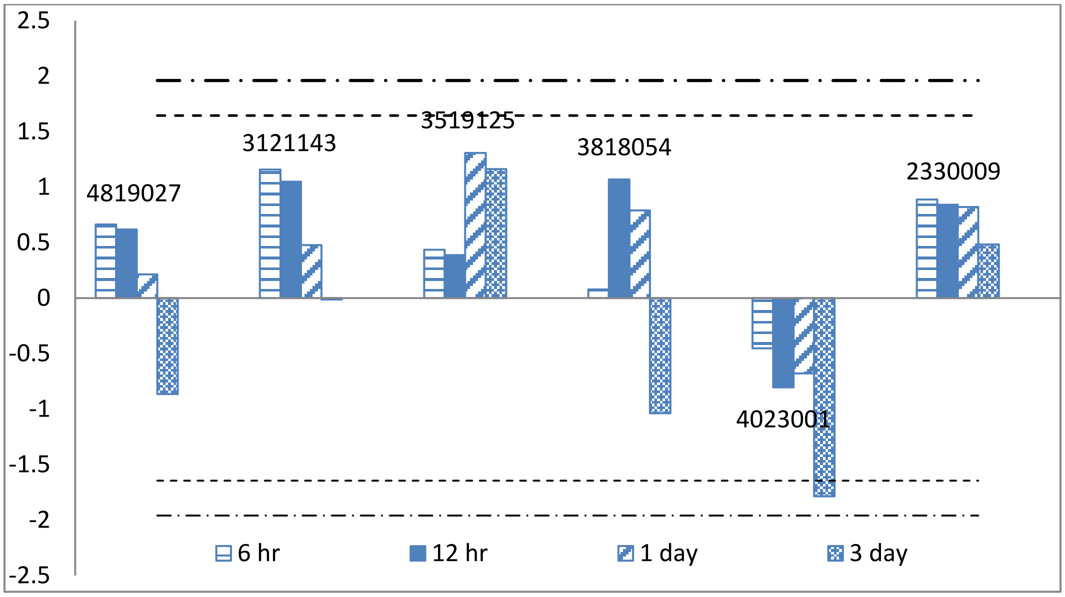

Table 9.X: Significance of trend in short-duration annual maximum rainfall for east coast region

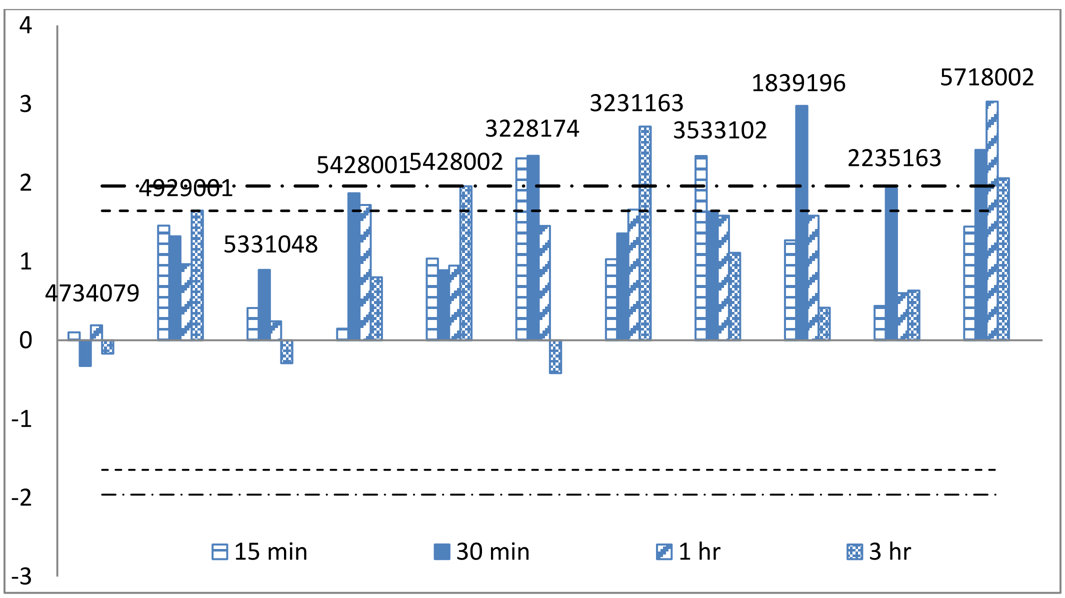

Table 9.Y: Significance of trend in long-duration annual maximum rainfall for east coast region