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Extreme Rainfall Non-Stationarity Investigation and Intensity-Frequency-Duration Relationship

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Extreme Rainfall Non-stationarity Investigation and Intensity-Frequency-Duration Relationship

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Abstract

Non-stationary behaviour of recent climate increases concerns amongst hydrologists about the currently used design rainfall estimates. Therefore, it is necessary to perform analysis to confirm stationarity or detect non-stationarity of extreme rainfall data in order to derive accurate design rainfall estimates for infrastructure projects and flood mitigation works. Extreme rainfall non-stationarity analysis of the storm durations from 6 min to 72 hours was conducted in this study using data from the Melbourne Regional Office station in Melbourne (Australia) for the period of 1925-2010. Stationary Generalized Extreme Value (GEV) models were constructed to obtain Intensity-Frequency-Duration relationships for the above storm durations using data of two time periods: 1925-1966 and 1967-2010 after identifying the year 1967 as the change point year. Design rainfall estimates of the stationary models for the two periods were compared to identify the possible changes. Non-stationary GEV models, which were developed for storm durations that showed statistically significant extreme rainfall trends, did not show advantage over stationary GEV models. There was no evidence of non-stationarity according to stationarity tests, despite the presence of statistically significant extreme rainfall trends. The developed methodology consisting of trend and non-stationarity tests, change point analysis, and stationary and non-stationary GEV models was demonstrated successfully using the data of the selected station.

Keywords: Extreme rainfall; trend analysis; non-stationarity; GEV.

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INTRODUCTION

Approximately 0.75°C global warming has been detected over the last 100 years. This warming cannot be explained by natural variability alone (Trenberth et al. 2007). The main reason for the current global warming is human activities resulting in extensive greenhouse gas emissions to the atmosphere (IPCC 2007). A major question, in the context of global warming, is related to the extreme rainfall events producing floods and droughts. Increases in frequency and magnitude of extreme precipitation events have already been observed in the rainfall records of many regions, irrespective of the mean precipitation trends. They have even occurred in some regions where the mean precipitation has shown decreasing trends (Tryhon and DeGaetano 2011).

IPCC (2007) reported that the intensity and frequency of extreme rainfall events are very likely to increase in the future with the exception in the regions that show very significant decreases in rainfall. Increases in frequency and magnitude of extreme precipitation events questions the stationarity in climate, which is one of the main assumptions of frequency analysis of extreme rainfalls. Possible violation of stationarity in climate increases concerns amongst hydrologists and water engineers about the currently used design rainfall estimates in infrastructure projects and flood mitigation works. Therefore, it is essential to perform analysis to confirm stationarity (or detect non-stationarity) of extreme rainfall data. Extreme rainfall trend analysis and non-stationarity tests are commonly used for detection of non-stationarity in hydrological studies (Wang et al. 2005; Rosenberg et al. 2010).

Several studies had been conducted to investigate extreme rainfall trends over different parts of the world (e.g. Goswami et al. 2006, Douglas and Fairbank 2011, Shang et al. 2011, Shahid 2011). Also, there had been many studies investigating rainfall trends in Australia (e.g. Collins and Della-Marta 2002; Smith 2004; Murphy and Timbal 2008; Barua et al. 2013). However, studies focusing on extreme rainfall trends in Australia are relatively limited. Haylock and Nicholls (2000) analyzed stations over eastern and south western Australia to determine trends in extreme rainfall events for the period 1910-1998 using three extreme rainfall indices: the number of events above a certain extreme threshold (extreme frequency), extreme intensity, and the ratio of contribution of extreme events to total rainfall (extreme percent). They stated extreme percent increases in Eastern Australia, whereas decreases in frequency and intensity of extreme events were found in southwest Western Australia. Li et al. (2005) investigated extreme rainfall events in southwest Western Australia using daily rainfall data and reported decreases in frequency and intensity of extreme events, similar to Haylock and Nicholls (2000). Groisman et al. (2005) reported an increasing trend in number of days with heavy rainfalls (greater than 99.7 percentile) in south eastern Australia. Gallant et al. (2007) examined rainfall trends including extreme events (95th and 99th percentiles) over two periods (i.e. 1910-2005 and 1951-2005) using data from 95 stations for six regions in southwest and east of Australia. They reported significant decrease in extreme rainfalls in the eastern cost in particular during summer and winter seasons after 1950.

Almost all above studies examined trends using daily rainfall data. However, extreme rainfall trends can show large variations over short durations (Bonaccorso et al. 2005). Therefore, it is essential to conduct extreme rainfall trend analysis at finer temporal scales, since urban flash flooding is the product of heavy rainfalls over short durations. Studies addressing non-

stationarity in extreme rainfall events are very rare in the literature for sub-daily temporal scales (Bonaccorso et al. 2005, Rosenberg et al. 2010, Jacob et al. 2011 a,b).

Extreme rainfalls are the essential inputs to develop Intensity-Frequency-Duration (IFD) curves, which are used to derive design rainfalls for infrastructure project designs and flood mitigation works (Rosenberg et al. 2010). The Australian Rainfall and Runoff (ARR) has been widely adopted as the guideline for design rainfall estimation in Australia (IEA 1987). The current IFD curves have not been updated in ARR since its 1987 edition. Data up to 1983 have been employed in these IFD curves. Influence of the data for almost 3 decades since 1983, in which effects of global warming has been discussed more intensively and justified by observed data (IPCC 2007), has not been taken into account in these IFD curves. Therefore, it is necessary to investigate the accuracy and reliability of current design rainfall estimates of ARR by developing methodologies using extended rainfall along with a much better understanding of climate and climatic influences. It should be noted that the Australian Bureau of Meteorology (BoM) is currently undertaking a project to update IFD information across Australia using also the most recent rainfall data (ARR 2012). However, no further information about the outputs of the project is publically available. Moreover, any information could not be found if this project assumes stationary climate, or non-stationarity tests will be applied to determine if climate is stationary or not.

In this paper, it is aimed to investigate extreme rainfall non-stationarity through trend analysis and non-stationarity tests. The extreme rainfall trend analysis was performed first for storm durations of 6, 12, 18, and 30 minutes, and 1, 2, 3, 6, 12, 24, 48 and 72 hours considering a rainfall station in Melbourne, Australia. Then, non-stationarity analysis of the extreme rainfall data was carried out using statistical and graphical tests in order to check if the

detected trends may correspond to extreme rainfall non-stationarity. Thereafter, potential effects of the climate change and variability on the IFD relationship (curves) were investigated through Generalized Extreme Value (GEV) distribution models. Expected rainfall intensities for return periods of 2, 5, 10, 20, 50 and 100 years were derived and compared for two time slices: 1925-1966 and 1967-2010, after identifying 1967 as the change point for extreme rainfall data for majority of the storm durations. Developed IFD curves were compared with the currently used ARR curves to investigate the validity of the ARR design rainfall estimates. Moreover, for storm durations, which showed statistically significant extreme rainfall trends, non-stationary GEV distribution models were developed and superiority of non-stationary models over stationary models were examined.

To the best knowledge of the authors, the studies by Jacob et al. (2011 a,b) are the only studies available in the literature investigating the potential effects of climate change and variability on rainfall IFD relationships in Australia, considering possible non-stationarity of extreme rainfall data in design rainfall estimates. However, Jacob et al. (2011 a,b) did not develop non-stationary extreme rainfall models and investigate their performances over stationary models, as it is done in this study. Therefore, this study has a potential not only to increase the understanding of climate change and extreme rainfalls, but also provide a contribution to the policy makers and the practitioners for infrastructure project design and flood mitigation works through developed methodology to get more accurate IFD curves and design rainfall estimates.

STUDY AREA AND DATA

The Melbourne City in Australia was selected as the study area. Data for the study was obtained from the Melbourne Regional Office rainfall station (Site no: 086071, Latitude: 37.81 °S Longitude: 144.97 °E) due to availability of long rainfall records, which is essential for trend and extreme rainfall IFD analysis. The Melbourne Regional Office rainfall station is located in an urbanized area. Therefore, urban heat island effect may have some effect on rainfall records of this station. However, investigation of urban heat island effects on rainfall records is beyond the scope of this study. Location of the Melbourne Regional Office rainfall station is shown in Fig.1.
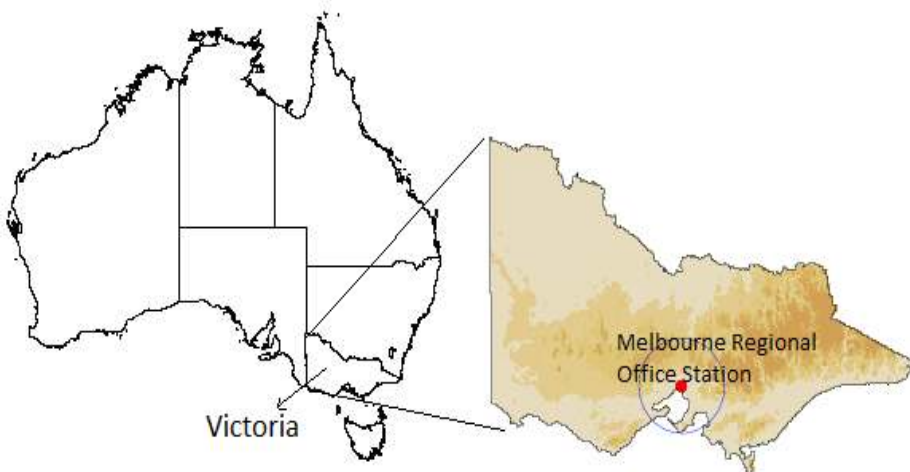

Fig. 1. Location of the Melbourne Regional Office Station

Six minutes pluviometer data were available from April 1873 to December 2010 at the Melbourne Regional Office rainfall station. These data were used to generate the annual maximum sub-daily and sub-hourly rainfall intensities for various durations (6, 12, 18 and 30 minutes, and 1, 2, 3, 6 and 12 hours). Moreover, daily data were available since April 1855, which were employed in this study to compute 24, 48 and 72 hour annual maximum rainfall intensities. Although there are no missing data in daily rainfall record, missing periods were found in 6 minutes data. There was a missing data period from January 1874 to July 1877 and

also from July 1914 to December 1924 during the World War I. Therefore, data between 1925 and 2010 were used for the purposes of this study for all storm durations. All above data were obtained from BoM.

METHODOLOGY

The methodology of this study consists of three parts, and the followed procedure is defined below.

(1) Trend analysis was first performed for various storm durations using non-parametric tests. Stationarity analysis was then carried out through statistical and graphical tests.

(2) Stationary GEV (GEV_S) models were developed, and design rainfall estimates were derived for standard return periods considering two time slices (1925-1966 and 1967-2010) after identifying 1967 as the change point. These design rainfall estimates were compared with those obtained using IFD tool developed by BoM based on the ARR guidelines.

(3) Non-stationary GEV (GEV_{NS}) models were constructed for the storm durations, that showed statistically significant extreme rainfall trends, and the advantages of GEV_{NS} models over GEV_S models were evaluated.

Trend Tests

Statistical tools that are used to detect time series trends are broadly grouped into two categories: parametric and non-parametric methods. Non-parametric tests are more appropriate for hydro-meteorological time series data, which are generally non-normally distributed and censored (Bouza-Deano et al. 2008). Mann-Kendall (MK) and Spearman's

rho (SR) are well-established non-parametric tests for trend detection (Yue et al. 2002), and were used to detect the trends of extreme rainfalls in this study.

MK and SR tests are rank based tests which have been commonly applied to hydro-meteorological time series data to detect trends (Tayanc et al. 2009; Mohsin and Gough 2009; Yue et al. 2002; Bouza-Deano et al. 2008). As they are non-parametric tests (i.e. distribution-free tests), they do not need to satisfy the normal distribution assumption of data, which is a basic assumption for parametric tests (Kundzewicz and Robson 2000; Novotny and Stefan 2007). Formulation and details of the MK and SR tests can be found in Kundzewicz and Robson (2000).

Although MK and SR tests are free of normally distributed data assumption, data independency remains as an assumption of these tests. The presence of serial dependence increases the probability of rejecting the null hypothesis (no trend). Hence, it may result in detection of the trends with a higher significance level than it would be if the series are independent. Therefore, it is essential to remove autocorrelation from data before using them in MK and SR tests for detection of trends. Von Storch (1995) proposed a method named pre-whitening to remove undesired influence of data dependence (Bayazit and Onoz 2007). Autocorrelated series in this study were pre-whitened using the method by von Storch (1995):

$$y_j = x_j - \rho x_{j-1} \tag{1}$$

where y_j is the pre-whitened data series, and ρ is the lag-1 autocorrelation coefficient (Willems et al. 2012). Trend tests (i.e. MK and SR tests) were then applied to the modified time series data.

Non-Stationarity Analysis

The purpose of a trend test is to determine if the time series has a general increase or decrease. However, increasing or decreasing behaviour of the series does not always indicate non-stationarity. When the purpose is to identify non-stationarity in time series, it is necessary to conduct further analysis. Therefore, three statistical tests, which are augmented Dickey-Fuller (ADF), Kwiatkowski–Phillips–Schmidt–Shin *(KPSS)* and Phillips-Perron (PP), were adopted in this study to investigate non-stationarity in extreme rainfall time series data. These tests were selected due to their common use in hydrological studies (Wang et al. 2005; Wang et al. 2006; Yoo 2007). The null hypothesis of ADF and PP tests is non-stationarity of the time series data, whereas the null hypothesis of the KPSS test is stationarity of the data series. Tests were conducted at 0.05 confidence level. Whenever the p-value (probability) of the test statistic is lower than the confidence level, the null hypothesis is rejected. Details of these tests can be found in Sen and Niedzielski (2010) and van Gelder et al. (2007).

In addition to these statistical tests, non-stationarity analysis was performed by autocorrelation coefficient function (ACF) plots. ACF plot consists of the pairs of autocorrelation coefficient (r_k defined in Equation (2)) and time lags (in horizontal axis).

$$r_k = \frac{\sum_{t=1}^{N-k}(X_t - \overline{X})(X_{t+k} - \overline{X})}{\sum_{t=1}^{N}(X_t - \overline{X})^2} \qquad k = 0,1, \ldots, N \qquad (2)$$

In Equation (2), N corresponds to the total length of the record and k is the lag time. X_t is the observation at time t and $\overline{X}$ is mean of series. If aurocorrelation coefficient shows quick decay to zero in ACF plot, it indicates the stationarity in time series. If there is a slow decay

in ACF plot (strong dependence), the time series data set has an evidence of non-stationarity (Modarres and Dehkordi 2005).

Change Point Analysis

Change point analysis was performed in this study to determine the time periods showing inhomogeneity (i.e. times of discontinuity in rainfall data), which might occur as a consequence of climate change, anthropogenic activities, and observational errors in monitoring, change in recording methodology or use of different equipment. It is possible to detect change point in a time series visually from time series graphs; however it is useful to employ a statistical approach for this purpose. The distribution free cumulative summation (CUSUM) test was recommended in many studies in literature to identify the change point in trend analysis (Kampata et al. 2008; Barua et al. 2013). Therefore, CUSUM test was adopted in this study for change point detection. Formulation of CUSUM test can be seen in Chiew and Siriwardena (2005).

Stationary and Non-Stationary Generalized Extreme Value Distribution Models

There are two basic methods to derive extreme rainfall data: 1) Block maxima, 2) Peaks over threshold (POT). In the block maxima approach, extreme rainfall data are obtained by selecting the maximum values from equal length blocks such as a year. On the other hand, the POT approach samples data above a certain threshold. Hence, it yields a larger sample size, but the extraction of data is more difficult than in the block maxima approach. Furthermore, careful attention should be given to ensure that data are independent in the POT approach. Using only one value from each block (year in this study) will result in small sample sizes, which could affect the accuracy of the parameter estimation of the extreme value distribution,

especially if the data record is short (Begueria et al. 2011). However, enough data (86 years of data) is available in this study. Also, the block maxima approach is more suitable than the POT approach, when independent data assumption of the extreme value analysis is considered. Therefore, the block maxima approach was employed to derive extreme rainfall data in this study.

There are two common distributions to fit the extreme rainfalls for frequency analysis in literature: i) Generalized Extreme Value (GEV) distribution and ii) Generalized Pareto (GP) distribution (Cooley 2009; Begueira et al. 2011). If data are obtained by the block maxima approach, several researchers (e.g. Sugahara et al. 2009; Park et al. 2011) recommended Generalized Extreme Value (GEV) distribution for extreme rainfall frequency analysis for both stationary and non-stationary cases.

The GEV distribution has three parameters including location (μ), scale (σ) and shape (ξ) parameters. The general form of the cumulative distribution function of the GEV distribution and detailed information on different types of GEV (i.e. Gumbel, Frechet and Weibull distributions) can be seen in Park et al. (2011).

Different approaches such as maximum likelihood and L-moments can be used to estimate parameters of the extreme value distribution. The L-moments method had been employed for parameter estimation of the stationary GEV models in this study since it is less affected from data variability and outliers, and relatively unbiased for small samples (Borijeni and Sulaiman 2009). Details of the L-moments method can be found in Yurekli et al. (2009).

Goodness of fit of the GEV models had been determined based on the graphical diagnostics and statistical tests. Common diagnostic graphs that were used for goodness of fit are the probability and the quantile plots. In these plots, observed values are plotted against the predicted values by the fitted model. In case of a good fit, points of the probability and the quantile plots should lie close to the unit diagonal. Although probability and quantile plots explain the similar information, different pairs of data were used in probability and quantile plots. It is useful to adopt both plots, since one plot can show very good fit while the other can show a poor fit. In this case, statistical tests are very helpful to determine if the fit is adequate. Details of the diagnostic graphs can be found in Coles (2001).

Kolmogorov-Simirnov (KS), Anderson-Darling (AD), and Chi-square (CS) statistical tests have been widely used in extreme value analysis studies in hydrological applications (Laio, 2004; Salarpour et al., 2012). Di Baldassarre et al. (2009) and Salarpour et al. (2012) explained the details of these statistical tests. These tests are used to determine if a sample comes from a hypothesized continuous distribution. Null hypothesis (H_0) is the data follow the specified distribution (which is GEV in this study). If the test statistic is larger than the critical value at the specified significance level, then the alternative hypothesis (H_A) (which is the data do not follow GEV distribution) is accepted. Both diagnostic graphs (probability and quantile plots) and statistical tests (KS, AD and CS) were used in this study.

It is useful to develop non-stationary GEV models, when there is evidence of statistically significant trends even if stationarity tests do not indicate non-stationarity. It is a common practice to incorporate time dependency into the location parameter of the GEV distribution in order to investigate how extremes are changing in time (Cooley 2009). Non-stationarity

can also be expressed using time dependency into scale parameter. It is quite difficult to estimate the shape parameter of the extreme values distribution with precision when it is time dependent, thereby; it is not realistic to attempt to estimate the scale parameter as a smooth function of time (Coles 2001).

In this study, three non-stationary models were developed with parameters as explained below:

- Model GEV_{NS1} $\mu_t = \beta_0 + \beta_1 t$, σ (constant), ξ (constant)

- Model GEV_{NS2} μ (constant), $\sigma(t) = \exp(\beta_0 + \beta_1 t)$, ξ (constant)

- Model GEV_{NS3} $\mu_t = \beta_0 + \beta_1 t$, $\sigma(t) = \exp(\beta_0 + \beta_1 t)$, ξ (constant).

In the above models, β_0 and β_1 modify the location and scale parameters of non-stationary GEV models to account for trend. It should be noted that the exponential function has been used to introduce trend in scale parameter to ensure the positivity of σ.

The maximum likelihood method was adopted for parameter estimation of GEV_{NS} models due to its suitability for incorporating non-stationary features into the distribution parameters as covariates, such as annual cycle and long-term trend (Sugahara et al. 2009). Readers are advised to refer to Shang et al. (2011) for details of the maximum likelihood method.

Superiority of GEV_{NS} models over GEV_S models were investigated through graphical tests: probability and quantile plots. In a non-stationary case, each data point has a different distribution associated with it; therefore it is essential to transform data in order to obtain the same distribution for each data point as explained in Coles (2001).

RESULTS AND DISCUSSION

Trend and Non-Stationarity Analysis

High lag-1 autocorrelation was detected for the data series of 6, 12 (0.05 significance level) and 18 minutes (0.1 significance level) storm durations, while the remaining storm durations did not show any statistically significant autocorrelation. Autocorrelated series (6, 12 and 18 minutes) were pre-whitened using the method by von Storch (1995), which was explained in "Trend Tests" section.

Trend tests (i.e. MK and SR tests) were then applied to the modified 6, 12, and 18 minutes time series data and the original data sets of the remaining storm durations, which are considered to be independent. Trends analysis results are shown in Table 1.

Table 1. Trend analysis results

Duration	Test Statistics		Result
	Mann-Kendal	Spearman's Rho	
6 min	1.636	1.487	NS
12 min	2.486	2.277	S(0.05)
18 min	2.403	2.282	S(0.05)
30 min	2.641	2.501	S(0.01) [MK], S(0.05) [SR]
1 hr	1.958	1.894	S(0.1)
2 hr	0.884	0.923	NS
3 hr	0.399	0.429	NS
6 hr	0.168	0.146	NS
12 hr	-0.854	-0.791	NS
24 hr	-0.123	-0.13	NS
48 hr	-0.586	-0.588	NS
72 hr	-0.962	-0.923	NS

Critical Values at 0.1, 0.05, and 0.01 significance levels are 1.645, 1.96, and 2.576 respectively.

S = statistically significant trends at different significance levels shown within brackets.

NS = statistically insignificant trends even at 0.1 significance level.

As can be seen from Table 1, MK and SR tests showed that extreme rainfall data for short storm durations of 12, 18, 30 minutes and 1hr exhibited statistically significant increasing trends at different significance levels. Although there is an increasing trend for the data sets of 6 min, 2, 3, and 6 hours, trends are not significant even at 0.1 significance level. The 12, 24, 48, and 72 hours extreme rainfall data sets demonstrated statistically insignificant decreasing trends. Trends in short (in particular sub-hourly) and long storm durations were largely different in terms of direction (positive or negative) and statistical significance. Time series plots of the data set of all storm durations are illustrated with linear trend lines in Fig. 2.
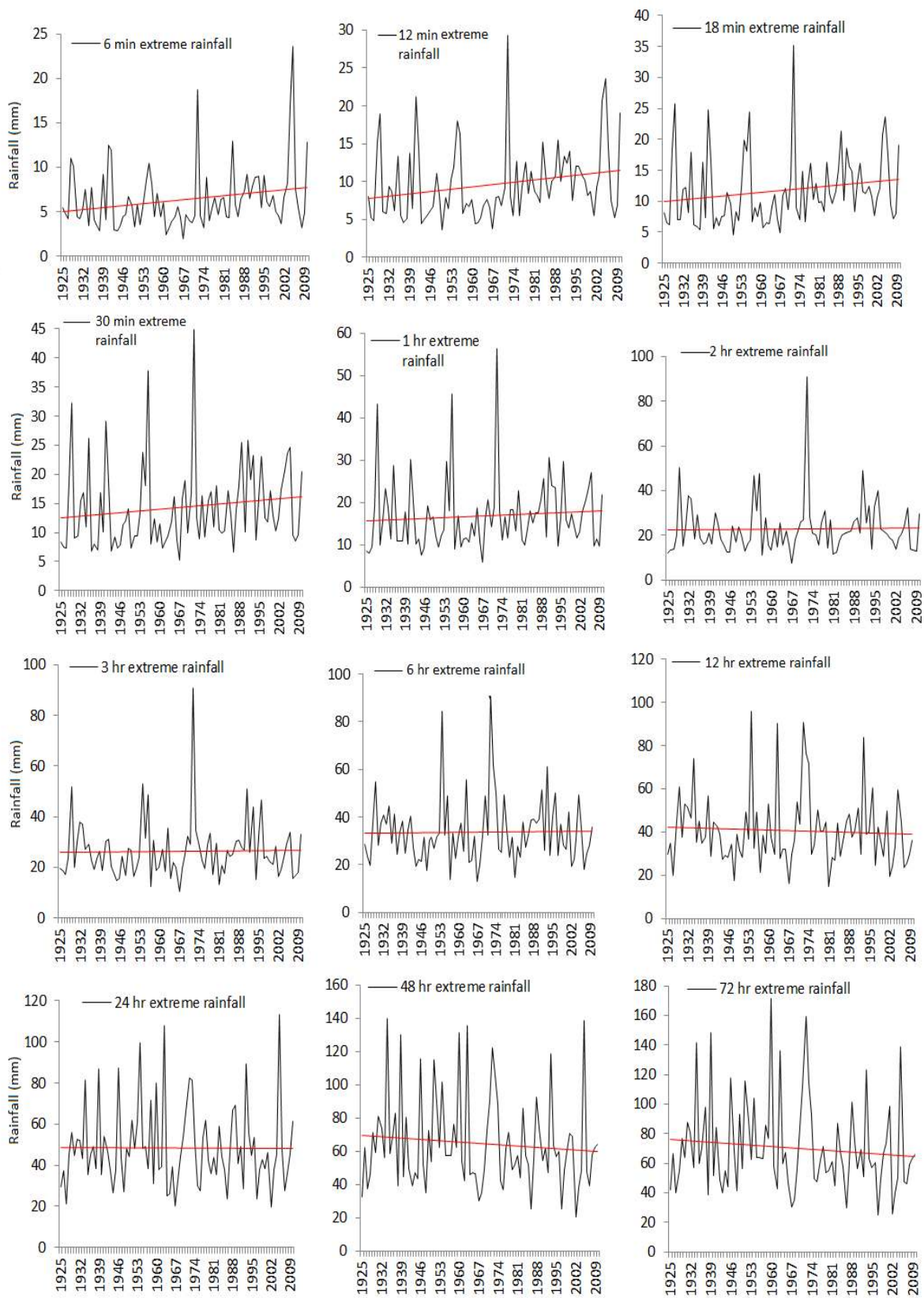
Fig. 2. Time series graphs of all storm durations

Although detected statistically significant trends may be a sign of non-stationarity of extreme rainfalls, trends do not necessarily mean non-stationarity. Thus, non-stationarity of extreme rainfall data was further investigated using graphical method and statistical tests as explained in "Non-stationarity Analysis" section. The ACF plots demonstrated relatively quick decay to zero rather than a slow decay, which is an indicator of stationarity (Fig. 3). However, there is still a need for objective statistical tests in order to decide if the data is stationary or non-stationary. All objective statistical tests (ADF, KPSS and PP) used in this study did not show any evidence of non-stationarity of extreme rainfalls.
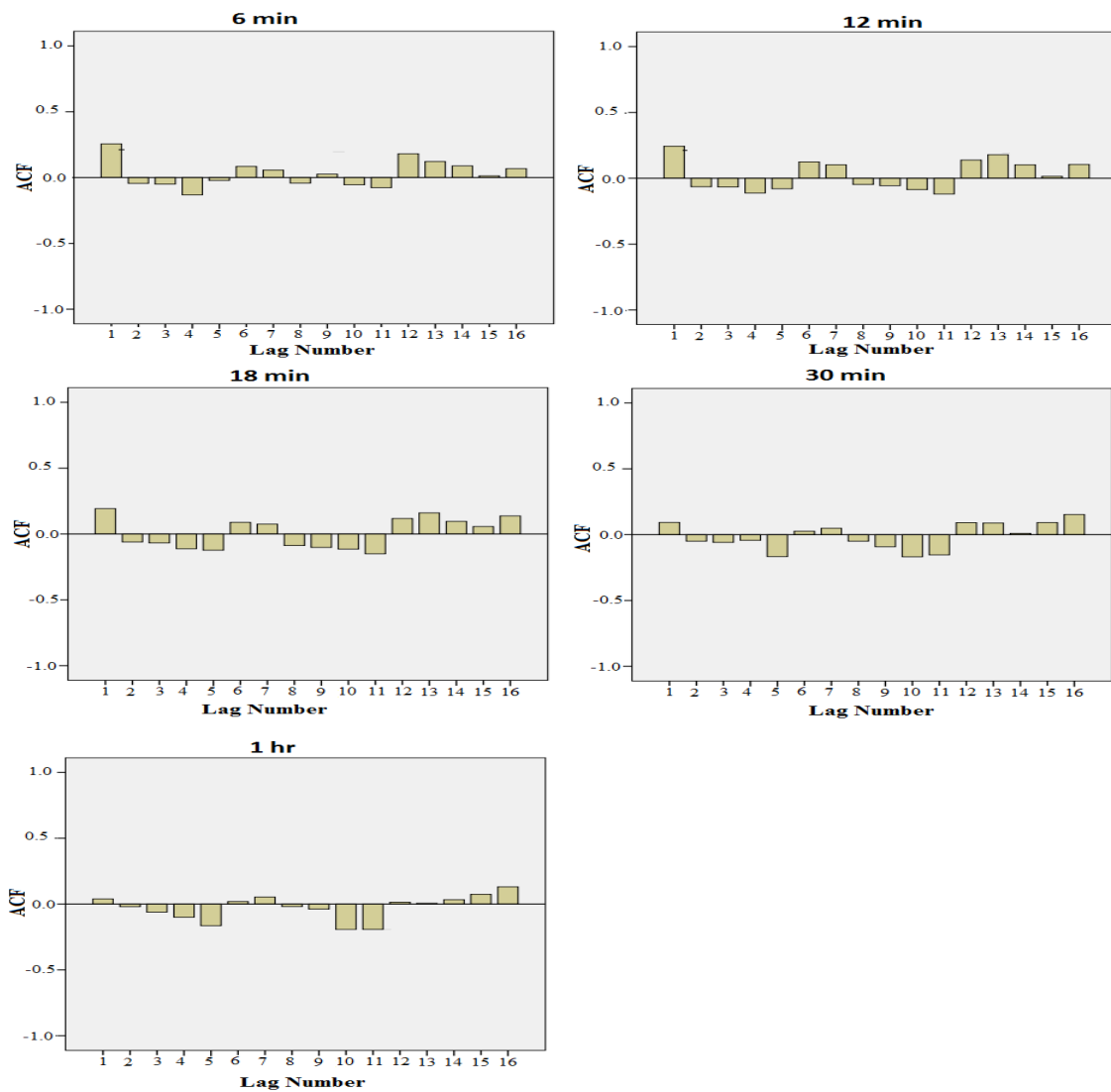

Fig. 3. ACF plots for sub-hourly storm durations

Design Rainfall Estimates Based on GEV$_S$ Models and Comparison between Stationary and Non-stationary GEV Models

GEV$_S$ models were constructed in order to derive IFD relationships for two time slices, which were determined based on change point analysis. Table 2 shows the results of the change point analysis using the CUSUM test for all storm durations. As can be seen from Table 2, change point of the majority of the storm durations oscillated around late 1960s. The 1967 year was selected as the change point year in this study based on the CUSUM results (Table 2). The IFD relationships were then derived for the two time slices: 1925-1966 and 1967-2010. Jones (2012) stated the period 1910-1967 as stationary and 1968-2010 as non-stationary according to the observed maximum and minimum temperature and rainfall data in south eastern Australia which includes the Melbourne region. Therefore, the findings of the change point analysis of this study are consistent with those of Jones (2012). However, the study did not show non-stationarity in extreme rainfalls for any time periods (i.e. 1925-2010, 1925-1966 or 1967-2010) and for any storm durations according to single station data.

Table 2. Change point year based on the CUSUM test

Storm Durations	Change Point
6 min	1977
12 min	1970
18 min	1967
30 min	1967
1 hr	1967
2 hr	1968
3 hr	1968
6 hr	1968
12 hr	1969
24 hr	1960
48 hr	1987
72 hr	1960

It should be noted that data independence is an assumption of GEV distribution. Therefore, the autocorrelation test was applied to the extreme rainfall data set of two periods: 1925-1966 and 1967-2010 to check the presence of time dependency of data. The autocorrelation test results showed that data for both time periods are independent and suitable to be used in GEV analysis.

The main purpose of developing stationary models was to compare expected rainfall intensities from GEV_S with the currently used design rainfall estimates based on the ARR guideline (which were also calculated under the stationary climate assumption). Moreover, the comparison of the design rainfall intensities in 1925-1966 and 1967-2010 (warmer period) periods could show the likely effects of climate change and variability on extreme

rainfall IFD relationships. Table 3 demonstrates the expected design rainfall intensities of GEV$_S$ models for the two time slices and using the ARR guideline for return period of 2, 5, 10, 20, 50 and 100 years, while Fig. 4 shows the same information graphically. Fig. 4 also shows 95% confidence limits of the design rainfall estimates corresponding to the two time slices. It should be noted that rainfall intensities in Fig.4 is shown in logarithmic scale to be able to detect differences more clearly.

Table 3. Expected rainfall intensities (mm/hr) of GEV$_S$ and ARR models

Durations/Return Periods	2 year			5 year			10 year		
	1925-1966	1967-2010	ARR	1925-1966	1967-2010	ARR	1925-1966	1967-2010	ARR
6 min	49.4	57.9	59.2	71.9	87.9	81.3	89.8	114.5	96.7
12 min	35.5	47.6	45.3	52.9	67.7	61.8	68.1	83.5	73.1
18 min	28.8	38.8	37.2	43.4	53.8	50.5	56.4	65.0	59.5
30 min	21.2	28.2	27.8	31.8	40.1	37.4	41.5	48.6	43.8
1 hr	13.0	16.1	18.5	19.2	22.6	24.7	24.9	27.4	28.8
2 hr	9.4	10.4	12	13.3	14.9	15.8	16.7	18.5	18.3
3 hr	7.6	8.2	9.23	10.3	11.4	12	12.4	13.8	13.9
6 hr	5.0	5.3	5.9	6.7	7.4	7.6	7.9	8.9	8.7
12 hr	3.0	3.1	3.8	4.1	4.3	4.8	5.0	5.2	5.5
24 hr	1.8	1.8	2.4	2.6	2.5	3.1	3.1	3.0	3.5
48 hr	1.3	1.2	1.5	1.8	1.6	1.9	2.2	1.9	2.3
72 hr	0.9	0.8	1.1	1.3	1.2	1.5	1.6	1.4	1.7

| Durations/Return Periods	20 year			50 year			100 year		
	1925-1966	1967-2010	ARR	1925-1966	1967-2010	ARR	1925-1966	1967-2010	ARR
6 min	109.4	146.8	117	139.1	201.1	147	164.9	253.7	171
12 min	85.9	100.8	88.1	115.4	126.8	109.9	143.2	149.4	132.2
18 min	72.2	76.9	71.5	98.9	94.0	88.8	124.9	108.3	103.0
30 min	53.7	57.1	52.5	74.9	69.0	64.8	96.2	78.5	75
1 hr	31.8	32.4	34.3	43.8	39.6	42.1	55.7	45.6	48.5
2 hr	20.6	22.7	21.6	26.8	29.0	26.4	32.5	34.7	30.2
3 hr	14.7	16.4	16.4	18.1	20.3	19.9	21.0	23.7	22.7
6 hr	9.3	10.4	10.1	11.0	12.4	12.2	12.4	14.1	13.9
12 hr	5.9	6.1	6.4	7.4	7.2	7.7	8.7	8.2	8.7
24 hr	3.7	3.5	4.1	4.6	4.1	4.9	5.3	4.6	5.6
48 hr	2.6	2.3	2.6	3.3	2.7	3.2	3.9	3.1	3.6
72 hr	1.9	1.7	1.9	2.4	2.1	2.4	2.8	2.4	2.7
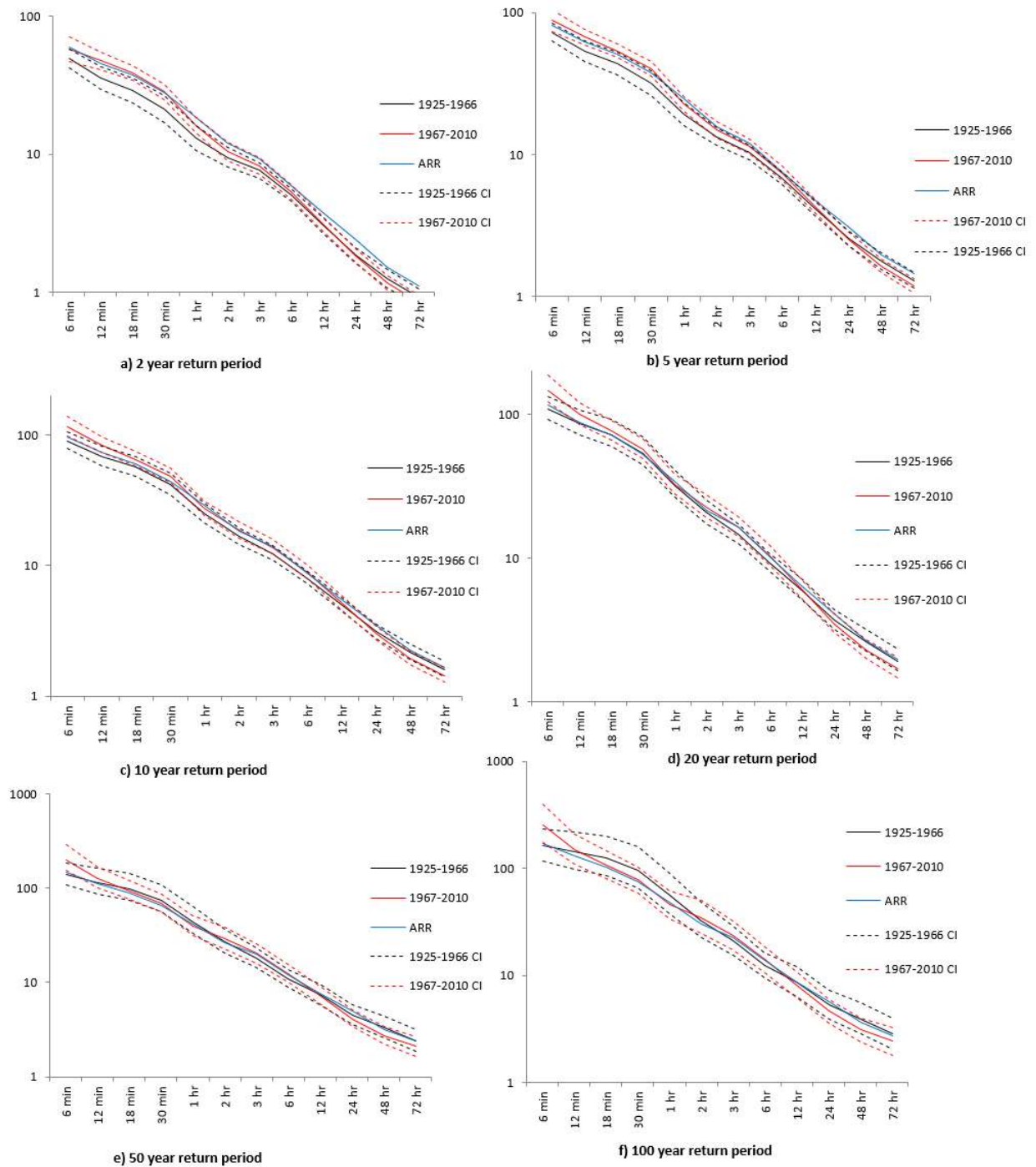
Fig. 4. Design rainfall estimates of GEV_S models and ARR (mm/h) for standard return periods

The ARR estimates fall between 1925-1966 and 1967-2010 GEV_S model estimates for all sub-hourly storm durations (except 6 min storm duration estimate for 2 years return period) for the return periods less than 20 years. For all return periods and sub-hourly storm durations

(again except 6 min storm duration estimate for 2 years return period), the ARR estimates were less than 1967-2010 GEV_S model estimates. Moreover, the ARR estimates were less than 1967-2010 GEV_S model estimates of 2, 3, and 6 hours storm durations for 20, 50, and 100 years return periods. For almost all the remaining return periods and the remaining storm durations, the ARR estimates are larger than those corresponding to 1967-2010 period.

Design rainfall estimates of the GEV_S models corresponding to the 1967-2010 period are larger than those corresponding to the 1925-1966 period for the durations from 6 min to 12 hr for the return periods less than 50 years (Table 3 and Fig. 4). This difference was clearer for sub-hourly estimates. The largest intensity differences between two periods of the GEV_S models were observed for the sub-hourly durations of the 2 and 5 year return periods (Fig. 4). The rainfall intensity estimates of the 1925-1966 GEV_S models were larger than of those corresponding to the 1967-2010 period for the durations 18 and 30 minutes, and 1, 12, 24, 48 and 72 hours in 50 and 100 year return periods conversely to the other return periods. The 1925-1966 model estimates were also slightly larger than those of the 1967-2010 period for 24, 48 and 72 hours storm durations of all return periods.

There can be two main factors for the large differences in design rainfall estimates and extreme rainfall trends corresponding to the above two time periods: (1) natural variability, and (2) climate change. Moreover, sampling error due to using data of only one station could be another reason. The El Nino-Southern Oscillation (ENSO) with El Nino and La Lina phases (Verdon et al. 2004), Indian Ocean Dipole (IOD) (Ashok et al. 2003), and the Southern Annual Mode (SAM) (Meneghini et al. 2007) were pointed as influential climate modes on the precipitation variability in Victoria (Australia), which includes the Melbourne region. However, Verdon-Kidd and Kiem (2009) explained that Inter-decadal Pacific

Oscillation (IPO) has a strong impact on the climate pattern change in Victoria. Moreover, Power et al. (1999) and Kiem et al. (2003) expressed that association between ENSO and Australian climate is modulated by IPO (Micevski et al. 2006). In particular, the relationship was strong during the IPO negative phases (i.e associated with wetter conditions). Kiem et al. (2003) showed La Lina events, which were enhanced during the negative IPO phases, as a primary driver for the flood risk.

Above studies suggest the need to investigate IPO effects on extreme rainfalls due to its direct effects on Australian climate as well as effects of IPO on ENSO, which has a strong link to Australian rainfall. The effects of IPO on extreme rainfalls were investigated in this study through average annual maximum rainfall intensity and extreme rainfall IFD relationship analysis during IPO negative and positive phases. Salinger (2005) and Dai (2012) expressed that 1947-1976 time period corresponds to the IPO negative phase, whereas 1977-1998 time period corresponds to the IPO positive phase. Therefore, extreme rainfall data set corresponding to these time periods (i.e. 1947-1976 and 1977-1998) were used for the analysis of IPO effects on extreme rainfalls. Table 4 shows the average annual maximum rainfall intensities during IPO negative and positive phases. As can be seen from Table 4, average annual maximum rainfall intensities of storm durations above 3 hr (i.e. 6, 12, 24, 48 and 72 hours) during the IPO negative phase were larger than those average annual maximum rainfall intensities for the IPO positive phase, and vice versa for the remaining storm durations.

Table 4. Average annual maximum rainfall intensities during IPO negative and positive phases

Storm Duration	Average Annual Maximum Rainfall Intensity (mm/hr)	
	IPO Negative Phase (1947-1976)	IPO Positive Phase (1977-1998)
6 min	55.3	67.8
12 min	43.2	53.9
18 min	36.1	43.1
30 min	27.8	30.6
1 hr	17.0	18.1
2 hr	12.0	12.3
3 hr	9.1	9.3
6 hr	5.9	5.8
12 hr	3.6	3.4
24 hr	2.1	2.0
48 hr	1.4	1.2
72 hr	1.1	0.9

Fig. 5 shows the findings of the extreme rainfall IFD relationship analysis during the IPO negative and positive phases. The design rainfall intensities of daily storm durations (24, 48 and 72 hr) for all return periods during the IPO negative phase were larger than those rainfall intensities during IPO positive phase. Moreover, the design rainfall intensities of all storm durations for the return periods equal to 20 yr and above (i.e. 20, 50 and 100 yr) during the IPO negative phase exhibited larger values relative to those rainfall intensities for the IPO positive phase as can be seen Fig. 5 (a). However, design rainfall intensities of sub-hourly storm durations for the return period less than 20 yr (i.e. 2, 5 and 10 yr) during IPO negative phase were lower than those design rainfall intensities for the positive phase as shown in Fig.5 (b).
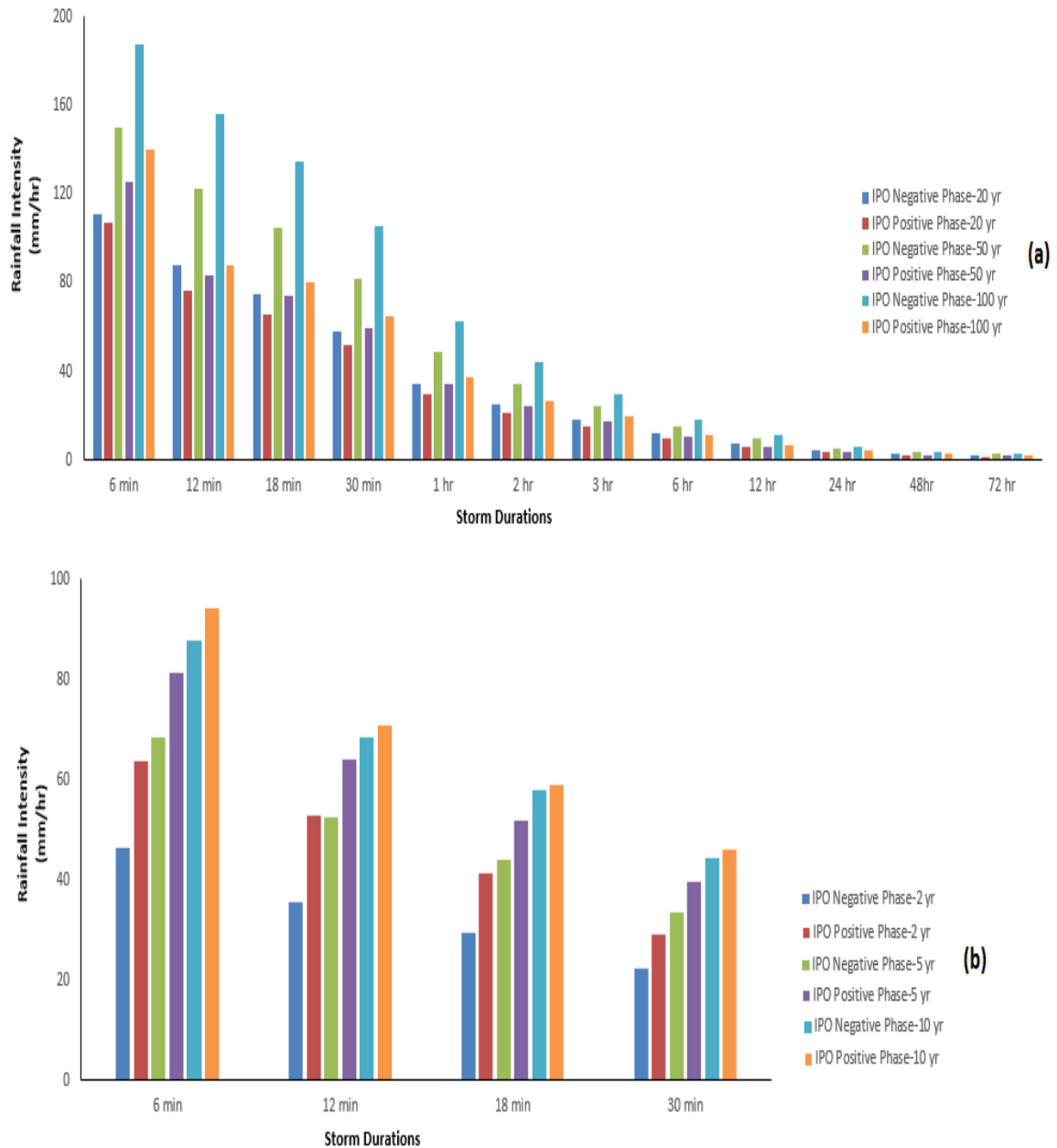
Fig. 5. IPO effects on design rainfall intensities during IPO negative and positive phases

In summary, as explained in literature, increases in extreme rainfalls were observed during the IPO negative phase for long storm durations and high return periods. However, extreme rainfall increases and differences in design rainfalls for short storm durations (in particular sub-hourly storm durations for short return periods) cannot be explained with the IPO influence only.

Anthropogenic climate change has a potential to affect not only extreme rainfalls directly but also the dynamics of key climate modes. A few studies (e.g. Murphy and Timbal 2008; CSIRO 2010) investigating rainfall changes in south eastern Australia mentioned that although there is no clear evidence to attribute rainfall change directly to the anthropogenic climate change, it still cannot be neglected. Change in rainfalls is linked at least in part to the climate change in south eastern Australia. However, it is very difficult to address anthropogenic climate change effects on possible shifts in the extreme rainfalls and climate modes due to the limited historical record and strong effects of natural climate variability (Westra et al. 2010). Further analysis to investigate the reasons of the rainfall trends and design rainfall differences is beyond the scope of this paper.

Table 5 demonstrates the KS, AD, and chi-square test statistics of the GEV_S models for both 1925-1966 and 1967-2010 periods along with critical values of the tests for the 0.05 significance level.

Table 5: KS, AD, and chi-square test statistics of the GEV$_S$ models

	1925-1966			1967-2010		
	KS	AD	Chi-Square	KS	AD	Chi-Square
Critical Values α(0.05)	0.20517	2.5018	9.4877	0.20056	2.5018	11.07
			Test Statistics			
Storm Durations	KS	AD	Chi-Square	KS	AD	Chi-Square
6 min	0.10372	0.34758	1.6904	0.06869	0.3022	3.8134
12 min	0.0895	0.44909	1.4106	0.07931	0.22656	1.4045
18 min	0.11472	0.72368	6.3524	0.05393	0.10776	0.23279
30 min	0.12311	0.54914	4.9254	0.091	0.37404	2.08
1 hr	0.1223	0.45773	0.5604	0.07692	0.27875	1.6087
2 hr	0.07806	0.23473	1.9473	0.1295	0.56989	3.5116
3 hr	0.09801	0.2368	8.8276	0.09546	0.44889	0.91735
6 hr	0.09487	0.2313	2.9333	0.06563	0.18716	2.667
12 hr	0.10241	0.38756	0.0907	0.0706	0.21466	0.89586
24 hr	0.09385	0.39002	1.8626	0.07754	0.25058	1.8309
48 hr	0.07859	0.28037	1.3606	0.09516	0.33122	3.4862
72 hr	0.07154	0.24746	1.7567	0.08847	0.46112	2.2291

As explained earlier, null hypothesis (i.e. the sample comes from the GEV distribution) is rejected if the test statistics are larger than the critical values. Smaller test statistics in Table 5 compared to the critical values, show that GEV distribution fits these data successfully. Diagnostic graphs also showed the successful fit for all storm durations. As an example, Fig. 6 illustrates the P-P and Q-Q plots for 72 hr duration GEV$_S$ model for the 1925-1966 period.
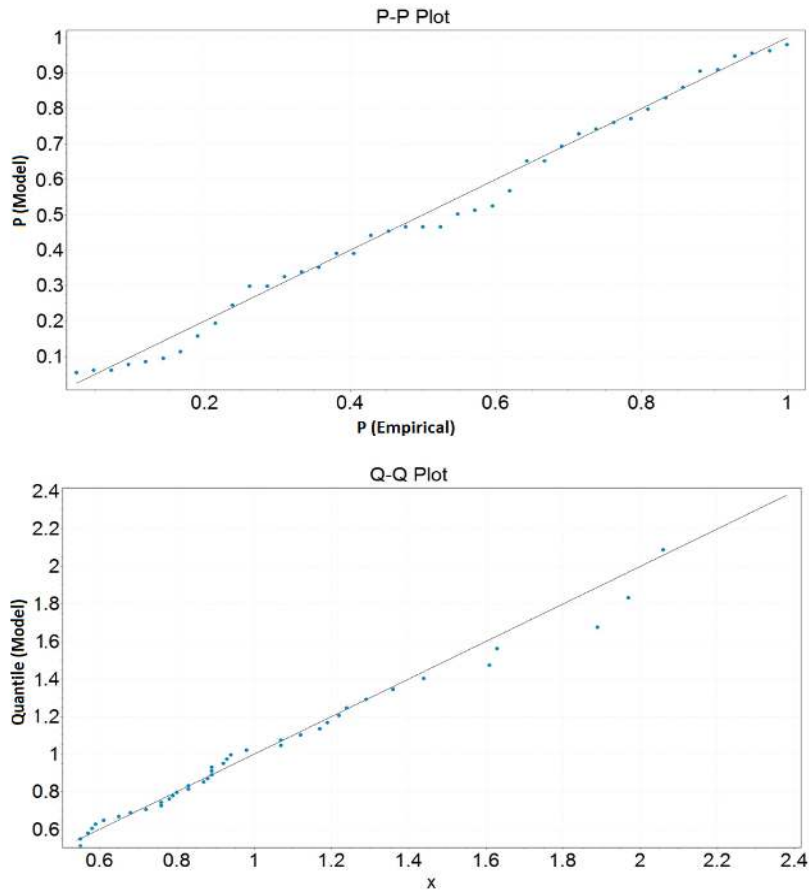
Fig. 6. Diagnostic graphs for 72-h duration GEV_S model

Non-stationary models (GEV_{NS1}, GEV_{NS2}, GEV_{NS3}) for the data showing statistically

significant trends (from 12 min to 1 hr) were developed for the same time slices (1925-1966

and 1967-2010) as GEV_S models. Diagnostic graphs showed that there is no evidence to

prefer non-stationary models over stationary models since the non-stationary models did not

result in better fit (lying close to the unit diagonal) than stationary models (Fig. 7). Fig. 7

shows the comparison of stationary and non-stationary GEV models in terms of diagnostic

plots for 30 min storm duration of the 1967-2010 time period. Fig. 7 demonstrates that

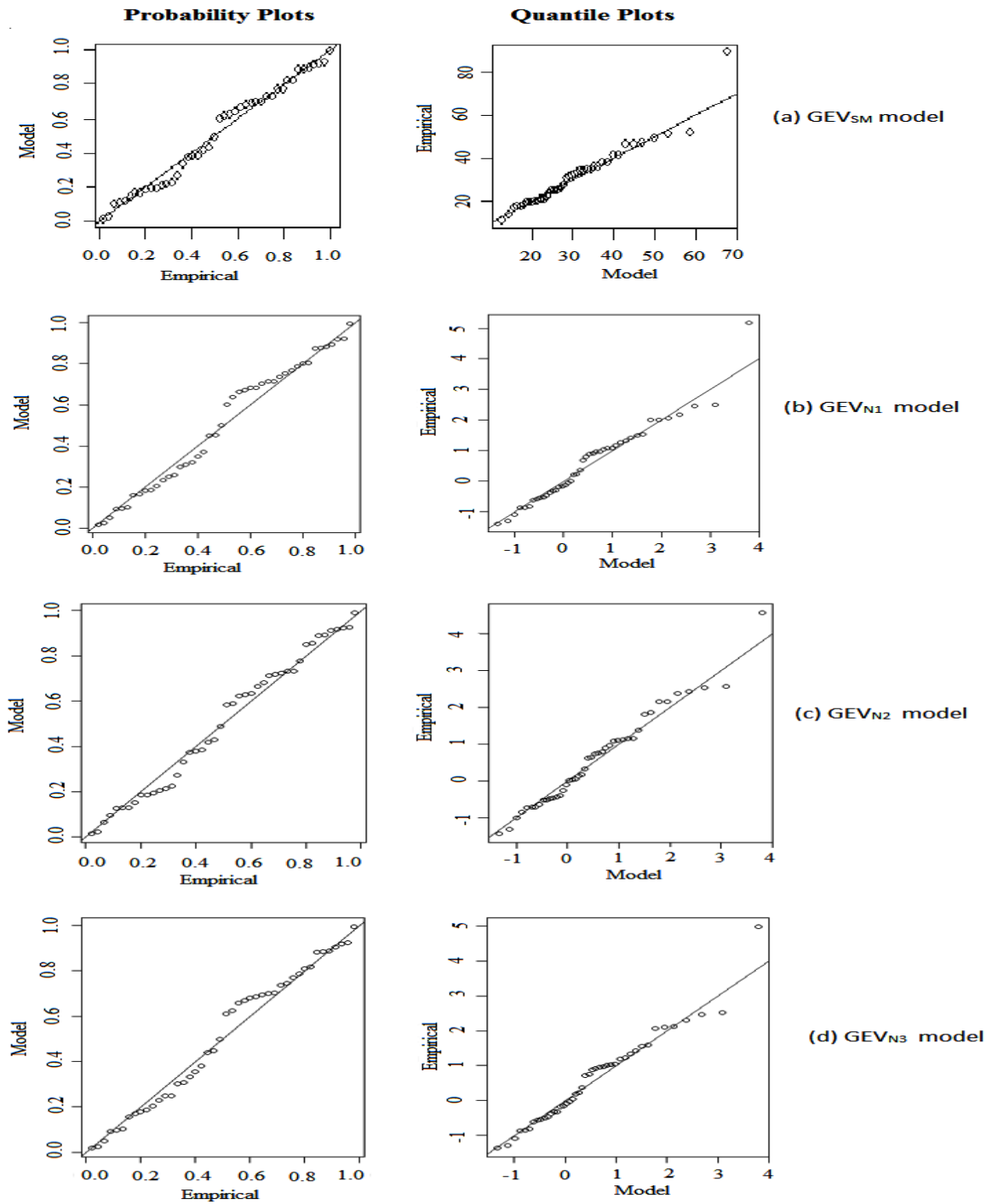stationary model (a) and non-stationary models (b,c,d) performances were very similar.

Fig. 7. 30-min stationary and non-stationary GEV model diagnostic graphs

CONCLUSIONS

A methodology consisting of trend and non-stationarity tests, change point analysis, and stationary and non-stationary Generalized Extreme Value (GEV) models was developed in

this paper to investigate the potential effects of climate change on extreme rainfalls and Intensity-Frequency-Duration (IFD) relationships. The developed methodology was successfully applied using extreme rainfall data of a single observation station in Melbourne (Australia). Same methodology can be used for other stations to develop larger spatial scale studies (using multiple stations' data). Followings are the major findings and conclusions of this study:

- Statistically significant extreme rainfall trends were detected for storm durations of 12, 18, and 30 minutes, and 1 hr, considering the data from 1925 to 2010.

- Despite to the presence of trends in extreme rainfall data for sub-hourly (except 6 min) and 1 hr storm durations, there was no evidence of non-stationarity according to graphical and statistical non-stationarity tests.

- The stationary GEV models were capable of fitting extreme rainfall data for all durations.

- Stationary GEV models' design rainfall estimates of 6 min to 12 hr storm durations for the return periods of 2, 5, 10, and 20 years over 1967-2010 period were larger than those estimates corresponding to the 1925-1966 period. The design rainfall estimates of the storm durations including 18, 30 minutes, and 1, 12, 24, 48, 72 hours for the 50 and 100 years return periods over the 1925-1966 period were larger than those estimates corresponding to the 1967- 2010 period.

- The design rainfall estimates derived based on the ARR were lower than the estimates of 1967-2010 models for sub-hourly durations in particular for 5, 10, and 20 years return periods.

- The developed non-stationary GEV models did not show any advantage over the stationary models.

- The above differences in design rainfall estimates between ARR and GEV models support the need to update the current Australian practice of estimating IFD information, including the most recent data.

- The above differences also suggest the need to conduct future Intensity-Frequency-Duration relationship studies using future climate data.

It should be noted that the findings of this study are based on data from a single station. One station was used in this study to demonstrate the methodology in this paper. It is not realistic to extrapolate the findings of this paper for larger spatial scales without further analysis using rainfall data from multiple observation stations.

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