1   **Regime shifts in Annual Maxima Rainfall across Australia– Implications**

2   **for Intensity-Frequency-Duration (IFD) relationships**

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20   **Abstract**

21   Rainfall Intensity-Frequency-Duration (IFD) relationships are commonly required for the

22   design and planning of water supply and management systems around the world. Currently

23   IFD information is based on the 'stationary climate assumption' - that weather at any point in

24   time will vary randomly and that the underlying climate statistics (including both averages

25   and extremes) will remain constant irrespective of the period of record. However, the validity

26   of this assumption has been questioned over the last 15 years, particularly in Australia,

27   following an improved understanding of the significant impact of climate variability and

28   change occurring on interannual to multidecadal timescales. This paper provides evidence of

29   regime shifts in annual maxima rainfall timeseries using 96 daily rainfall stations and 66 sub-

30   daily rainfall stations across Australia. Further, the effect of these regime shifts on the

31   resulting IFD estimates are explored for three long-term sub-daily rainfall records (Brisbane,

32   Sydney and Melbourne) utilising insights into multidecadal climate variability. It is

33   demonstrated that IFD relationships may under- or over-estimate the design rainfall

34   depending on the length and time period spanned by the rainfall data used to develop the IFD

35   information. It is recommended that regime shifts in annual maxima rainfall be explicitly

36   considered and appropriately treated in the ongoing revisions of Engineers Australia's guide

37   to estimating and utilising IFD information, 'Australian Rainfall and Runoff', and that clear

38   guidance needs to be provided on how to deal with the issue of regime shifts in extreme

39   events (irrespective of whether this is due to natural or anthropogenic climate change). The

40   findings of our study also have important implications for other regions of the world that

41   exhibit considerable hydroclimatic variability and where IFD information is based on

42   relatively short data sets.

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1. Introduction

Information on rainfall event intensity, frequency and duration (IFD, or IDF as it is known in some countries) plays a critical role in the design of dams, bridges, stormwater drainage systems and floodplain management. Dependent upon the application, information is required for event-durations ranging from hours to several days. The development of IFD relationships were first proposed by Bernard (1932) and since then different versions of this relationship have been developed and applied worldwide (e.g. Bara et al. 2009, Chen 1983, Hershfield 1961, IHP-VII 2008, Nhat et al. 2006, Raiford et al. 2007).

Historically, in Australia, IFD design rainfall curves were developed by the Australian Bureau of Meteorology (BoM) for durations ranging from 5 minutes to 72 hours and Average Return Intervals (ARI) of 1 year to 100 years (however, recently additional durations and ARIs have also been developed). Up until very recently IFD information available to (and used by) engineers and hydrologists were developed 25 years ago, as part of Engineers Australia publication Australian Rainfall and Runoff (AR&R) in 1987. New IFD information was released early in 2013 after a major revision of IFD information carried out by Engineers Australia. Importantly, the revised IFD information is based on a longer and more extensive rainfall data set (http://www.bom.gov.au/water/designRainfalls/ifd/). However, the BoM and Engineers Australia still recommend to use the AR&R 1987 information for existing flood studies and the probabilistic rational method and to conduct sensitivity testing with the revised 2013 AR&R parameters including the new IFD design rainfalls (http://www.bom.gov.au/water/designRainfalls/ifd/index.shtml).

At the time of writing, the revised IFD information does not take into account the impact of climate change on IFD estimates. This is part of ongoing research commissioned through Engineers Australia. It is also not yet clear how or if the role of natural climate variability is going to be considered. Of concern is the fact that currently, estimates of IFD are based on

69 the assumption that "climatic trend, if it exists in a region, has negligible effect on the design

70 intensities" (Pilgrim 1987). This is known as the 'stationary climate assumption' n (i.e.

71 thestatistical properties of the rainfall do not change over time) and implies that the chance of

72 an extreme event occurring is the same at any point in time (past or future). However, the

73 validity of this assumption has been questioned over the last 15 years following

74 demonstration of the significant impact of climate variability occurring on interannual to

75 multidecadal timescales in Australia. For example, research has shown that annual maximum

76 flood risk estimates in Australia vary depending on climate state (e.g. Ishak et al. 2013, Kiem

77 et al. 2003, Leonard et al. 2008). Importantly these studies demonstrate that founding flood

78 risk estimates on an unsuitable time period has the potential to significantly underestimate (or

79 overestimate) the true risks. This may apply to design rainfall also given that current IFD

80 estimates are based on varying lengths of data spanning different time periods (the latest IFD

81 estimates are based on all daily-read stations with 30 or more years of record and all

82 continuously-recording stations with more than 8 years of record).

83 Khaliq et al. (2006) explained that the traditional idea of probability of exceedance and return

84 period are no longer valid under non-stationarity. Recently, Jakob et al (2011a) found that

85 rainfall quantile estimates derived for Sydney Observatory Hill for the period 1976 to 2005

86 show significant decreases across durations from 6 minutes to 72 hours. Jakob et al (2011b)

87 subsequently extended the sub-daily rainfall data analysis to 31 sites located in southeast

88 Australia, assessing variations in frequency and magnitude of intense rainfall events across

89 durations from 6 minutes to 72 hours. This study identified two different trends in the data

90 sets, a decreasing trend in frequency of events at durations of 1-hour and longer for sites in

91 the north of the study region, while sites in the south cluster displayed an increase in

92 frequency of events, particularly for sub-hourly durations. Importantly Jakob (2011a, 2001b)

93 concluded that, for at least some regions of Australia, trends found in historical records has

94 the potential to significantly affect design rainfall estimates. Westra and Sisson (2011) also

95 investigated evidence of trends in extreme precipitation at sub-daily and daily timescales

96 (1965-2005) using a spatial extreme value model. They identified a statistically significant

97 increasing trend in precipitation extremes for the sub-daily data set, however at the daily

98 timescale no change in annual maximum rainfall could be detected with the exception of

99 southwest Western Australia (Westra and Sisson 2011). Further, Yilmaz and Perera (2014)

100 conducted change point analysis for extreme rainfall data for storm durations ranging from 6

101 minutes to 72 hours in Melbourne, and found evidence of regime shifts, concluding the year

102 1966 as a statistically significant change point. Yilmaz et al (2014) then investigated changes

103 in extreme rainfall through trend analysis, non-stationarity tests and non-stationary GPD

104 models (NSGPD) for Melbourne. They found statistically significant extreme rainfall trends

105 for storm durations of 30 minutes, 3 hours and 48 hours, however for above storm durations

106 there was no evidence of a regime shift (which they termed 'non-stationarity') according to

107 statistical non-stationarity tests and non-stationary GPD (Yilmaz et al (2014).

108 A limitation of the analysis presented by Westra and Sisson (2011) and Jakob et al (2011a,

109 2011b) is that they tested for linear trends in the rainfall data series based on the hypothesis

110 that extreme rainfall events would have either decreased, increased or exhibited no trend over

111 the time period being investigated. However these are not the only attributes of trend

112 detection, since annual rainfall maxima may also cycle through interannual to multidecadal

113 periods (note that Westra and Sisson (2011) also investigated possible links between extreme

114 rainfall and annual fluctuations in the El Niño/Southern Oscillation (ENSO)). Therefore,

115 depending on what time period the annual rainfall maxima data are derived from (in reference

116 to any long term cycles or epochs) the observed trends may be misleading or even not

117 apparent (leading to the misconception that regimes shifts are non-significant or not an

118 important consideration). Recently Yilmaz et al (2014) investigated the potential impact of

119   the Interdecadal Pacific Oscillation (IPO) on extreme rainfall and resulting IFD for a case

120   study in Melbourne. They concluded that, the IPO negative phase can be the driver of higher

121   rainfall intensities for long durations and high return periods. However, the trends in extreme

122   rainfall data and differences in rainfall intensities for short storm durations and return periods

123   could not be explained with the IPO influence. Given that Melbourne is located in south-east

124   Australia, where the influence of the IPO is temporally variable due to other climate drivers

125   operating (acting to enhance or suppress impacts, see Kiem and Verdon-Kidd 2010; 2009),

126   the research by Yilmaz et al (2014) provides promise for developing relationships between

127   extreme rainfall and the IPO for regions where the IPO may have a more consistent influence

128   (due to fewer competing climate modes), such as north-eastern Australia.

129   Therefore this paper aims to establish if there is evidence of regime shifts in the annual

130   maxima rainfall timeseries (1-hour to 7-days) across Australia by testing for shifts (regardless

131   of direction or timing) in the long term sub-daily and daily data. Further, the implications on

132   IFD estimation are explored, along with the potential influence of the IPO on extreme rainfall

133   and resulting IFD. Recommendations are then provided as to how these insights may be

134   incorporated in future revisions of AR&R.

135   **2.   Data and methods**

136   2.1   Data

137   2.1.1   Rainfall data

138   Sub-daily and daily rainfall data for Australia were obtained from the BoM. Sub-daily data

139   records from continuously recording (i.e. pluviograph) rainfall stations in Australia tend to be

140   relatively short, hindering the ability to conduct trend and attribution studies. In this study

141   pluviograph rainfall stations were chosen with data spanning at least 40 years and at least

142   90% complete, resulting in 66 stations (see Figure 1a). In order to address the concerns raised

143   in the Introduction about short term data analysis (note that according to Raiford et al. (2007)

144   ARI should not be extrapolated from more than twice the record length), three long-term data

145   sets, highlighted in Figure 1a, were chosen for further analysis that contained data from at

146   least 1913 onwards (Brisbane Aero, Sydney (Observatory Hill) and Melbourne Regional

147   Office).

148   Daily rainfall stations with data spanning the period 1900 to 2009 were selected in order to

149   capture as much temporal variability as possible (see Figure 1b). These stations were filtered

150   according to the amount of data missing in order to identify the highest quality stations

151   recording rainfall during this period, resulting in 96 being considered suitable for further

152   analysis. Due to variability in the quality and quantity of rainfall data in each State of

153   Australia, the following selection criteria were applied:

154   • New South Wales, Queensland and Victoria - selected stations are at least 97%

155   complete;

156   • Tasmania- selected stations are at least 90% complete; and

157   • South Australia, Northern Territory and Western Australia - selected stations are at

158   least 85% complete.

159   *****Figure 1 about here****

160   2.1.2   Climate index data

161   The climate of Australia has experienced a number of regime shifts in climate during its

162   history, resulting in sustained periods of above average rainfall and storminess and

163   abnormally cool temperatures, followed by the reverse conditions (i.e. droughts and elevated

164   bushfire risk) (e.g. Erskine and Warner 1988, Franks and Kuczera 2002, Kiem et al. 2003,

165   Kiem and Franks 2004, Verdon et al. 2004). These shifts have tended to occur every 20 to 30

166 years and are associated with changes in the Interdecadal Pacific Oscillation (IPO, Power et

167 al. 1999). The IPO represents variable epochs of warming (i.e. positive phase) and cooling

168 (i.e. negative phase) in both hemispheres of the Pacific Ocean (Folland et al. 2002).

169 Importantly, the IPO has been shown to influence the magnitude and frequency of flood and

170 drought cycles across eastern Australia (Kiem et al. 2003, Kiem and Franks 2004). In New

171 Zealand, the IPO is also associated with similar shifts in flood frequency (McKerchar and

172 Henderson 2003). It has been noted that, following the abrupt shift in the IPO in the mid

173 1970s, the period, amplitude, spatial structure and temporal evolution of ENSO markedly

174 changed (Wang and An, 2001). Historically, during negative phases of the IPO there tends to

175 be more La Niña (wet) events and fewer El Niño (dry) events (Kiem et al. 2003, Verdon and

176 Franks 2006), resulting in an overall 'wet' epoch for eastern Australia and New Zealand .

177 While during the positive phase of the IPO there tends to be a higher frequency of El Niño

178 events and fewer La Niña events (Kiem et al. 2003, Verdon and Franks 2006), resulting in an

179 overall 'dry' epoch. In this study negative phases of the IPO were defined as 1913-1920 and

180 1945-1977, while positive phases included 1921-1944 and 1978 to 2010.

181 2.2   Statistical tests

182 A 20 year moving window was used to test for low frequency variability in the annual

183 maxima timeseries (1-hour, 1-day and 7-day). A Mann-Whitney U test was then used to

184 determine the statistical significance of possible regime shifts by testing if the first 10 years

185 of data was significantly different from the second 10 years, within the 20 year window (the

186 null-hypothesis in this case was that the data was independently distributed). If the difference

187 in medians was found to be statistically significant (i.e. p-value < 0.05) and there was a

188 change in sign of the median values (e.g. switch from negative to positive), a climate shift

189 was postulated to have occurred during the 10th year of the window. The Mann-Whitney U

190 test is a robust test that does not place implicit assumptions on the underlying distribution of

191 the data (i.e. it is a distribution free test), which is particularly appropriate here due to the

192 small number of years used in each window (Kundzewicz and Robson 2004). Note that a

193 number of different size windows were also tested, however this did not change the results or

194 conclusions.

195 A second test was also applied to identify step changes in the 1-day and 7-day annual maxima

196 time series known as the distribution free CUSUM with resampling (note that the test was not

197 applied to the shorter sub-daily data as longer data sets are recommended for this method).

198 CUSUM tests whether the means in two parts of a record are different (for an unknown time

199 of change). The second test was applied as it does not require the use of a moving window

200 (which is a limitation of the Mann-Whitney U test described above). However the CUSUM

201 test sequentially splits the timeseries into two potions (which are not necessarily equal),

202 which may be a problem if more than one cycle/shift is present in the timeseries.

203 The existence of serial correlation (or autocorrelation) in a time series will affect the

204 ability of tests (such as the Mann-Whitney U and CUSUM) to assess the site

205 significance of a trend (e.g. Yu et al. 2003, Serinaldi and Kilsby 2015b). The presence

206 of cross-correlation among sites in a network will also influence the ability of the test

207 to evaluate the field significance of trends over the network (e.g. Yu et al. 2003,

208 Douglas et al. 2000, Guerreiro et al. 2013). Therefore, prior to applying the change point

209 analysis as described above, the Durbin-Watson (DW) statistic was used to test for

210 autocorrelation in the annual maxima timeseries (Durbin and Watson (1950, 1951)). In this

211 case the null hypothesis is that the residuals from an ordinary least-squares regression are not

212 autocorrelated against the alternative that the residuals follow an AR1 process. All DW

213 statistic values were found to be greater than the 1.562 (the upper bound for 1% significance

214 and a sample size of ~100) providing no evidence to reject the null hypothesis. Therefore,

215 any regime shifts detected using the change point methods above are not likely to be artefacts

216 resulting from hidden persistence.

217 The potential issue of cross- correlation was also investigated. It was found that less than 9%

218 of all possible pairings of rainfall data sets display a significant (yet weak) correlation at the

219 5% level (r >0.2, significance based on n=100). Only eight pairings (out of 4465) were

220 correlated at 0.5 or higher. It was also found that stations located more than 500km apart

221 were unlikely to be correlated and that the strength of the correlation reduced as distance

222 increased between the pairs. This is not surprising given annual maximum rainfall events are

223 due to synoptic scale processes. Therefore observations relating to spatial consistency of

224 regime shifts are unlikely to be due to spatial correlation between sites.

225 ## 2.1   IFD Calculation

226 The standard process for obtaining IFD information for a location is to refer to the six master

227 charts of rainfall intensity for various durations and ARIs covering all of Australia in Volume

228 2 of AR&R 2001. Alternatively, IFD curves can be obtained for any location in Australia via

229 the BoM website (both the AR&R 1987 and revised IFDs are available). This information is

230 based on regionalised estimates of IFDs that are spatially and temporally consistent.

231 However, this approach cannot be adopted when using the instrumental rainfall data required

232 for the analysis presented in this study. As such, the IFD information generated for this

233 project follows the methodology on which the IFDs were based for AR&R 1999 which

234 utilises point source data with no regionalisation. It should be noted that it is not the purpose

235 of this paper to compare different methods of generating IFDs, rather, one method has been

236 adopted in order to provide a comparative assessment of the impact of non stationarity on

237 IFD estimation. The AR&R 1999 procedure used to generate IFDs from raw rainfall data (i.e.

238 point based estimates) is summarised as follows:

239   •   A log-Pearson III distribution was fitted to the annual maxima timeseries using the

240   method of moments (for annual maxima series of 30 minutes to 72 hours duration).

241   This is the standard distribution that has historically been adopted for generating IFDs

242   in Australia; however other distributions have recently been tested as part of the

243   revision of AR&R. To test if this distribution is suitable for the region being studied,

244   the goodness of fit for the log-Pearson III was tested using a Kolmogorov Smirnov

245   (KS) test. Here the null hypothesis is that the data fits the Log-Pearson lll distribution

246   (the alternate is that the data does not follow the Log Pearson III distribution). All p-

247   values were greater than 0.05 (average p-value was 0.75), for all series (30min to 72hr

248   durations at Brisbane, Sydney and Melbourne), therefore we accept the null

249   hypothesis at the 5% significance level.;

250   •   The coefficient of skewness was determined for each duration (30 minutes to 72

251   hours);

252   •   The coefficient of skewness was then used to obtain a frequency factor, K_Y, for use

253   with Log-Pearson III Distribution. K_Y was obtained from Table 2.2 (positive skew

254   coefficients) and Table 2.3 (negative skew coefficients) in AR&R 1999 Book 4;

255   •   Rainfall intensities for a range of ARI were calculated using the following formula:

256   • $\log RI_Y = M + K_Y S$ (1)

257   Where: RI_Y = rainfall intensity having an ARI of 1 in Y

258   M = mean of the logarithms of the annual maxima rainfalls

259   S= Standard deviation of the logarithms of the annual maxima rainfalls

260   K_Y = frequency factor for the required ARI of 1 in Y

261   •   ARIs of 2 years to 10 years were adjusted to partial-duration series estimates. In

262   AR&R 1999, the following correction factors were used (note: for ARI greater

263   than 10 years, no corrected factor is required): 2 year ARI – 1.13, 5 year ARI -

264   1.04, 10 year ARI – 1.0.

265   It should be noted that this approach is likely to result in different estimates of IFDs than

266   those obtained from the standard maps provided by AR&R 1999 or the revised IFD

267   estimates released in 2013. Here we are using point based rainfall data, whereas AR&R

268   1999 have derived regionalised estimates based on multiple rainfall stations with varying

269   lengths of data, varying resolution (daily and pluviograph) and varying quality of records.

270   It is recognised that analysis of rainfall data from single stations is often unreliable, is not

271   temporally or spatially consistent and should generally not be used for design purposes.

272   However, the use of point based rainfall data satisfies the specific aims of this study

273   (which is a comparative analysis) and is therefore considered appropriate.

274   **3. Results**

275   3.1   Test for regime shifts in the annual maxima rainfall timeseries

276   Significant step changes identified in the extreme rainfall timeseries are shown in Figure 2.

277   Of the 66 sub-daily rainfall stations tested, 40 (61%) displayed at least one step change in the

278   1-hour annual maxima timeseries (Figure 2a), with some stations exhibiting multiple shifts.

279   Of the 96 daily rainfall stations tested, 86 displayed at least one step change in the 1-day

280   annual maxima timeseries (Figure 2b), while 92 exhibited at least one shift in the 7-day

281   annual maxima timeseries (Figure 2c), and some stations exhibited multiple shifts. Figure 2

282   collectively shows that observed step changes (or regime shifts) in annual maxima rainfall are

283   not confined to any one particular region of Australia, with most stations analysed exhibiting

284   at least one statistically significant shift.

285   ****Figure 2 about here****

286   As shown in Figure 3, the CUSUM test yielded fewer stations with statistically significant

287   step change in the annual maxima timeseries (only 18 stations out of 96) and many of these

288   were clustered along the coastal fringe of eastern Australia (note that, although the total

289   number of stations displaying significant change points was the same for both the 1-day and

290   7-day annual maxima, in some cases the location of the stations differed between the two).

291   However, as stated previously a limitation to this method is that only one significant change

292   can be detected using the CUSUM test (given that the data is sequentially split into two

293   portions during testing). This can be a problem if more than one step change or cycle in the

294   data is present (see example timeseries in Figure 4). Therefore, while the number of stations

295   displaying a step change is reduced using the alternative method, the results do in fact support

296   the theory that regime shift(s) in the annual timeseries are present for some stations at

297   different durations.

298   ****Figure 3 about here****

299   ****Figure 4 about here****

300   The temporal consistency of step changes in the annual maxima timeseries was further

301   investigated (Figure 5a) and it was found that the timing of observed shifts were not

302   necessarily consistent across Australia. However, for some regions (e.g. the east coast of

303   Australia) periods such as the 1940s (Figure 5b) and to a lesser degree 1970's (Figure 5c)

304   display a higher degree of spatial consistency.

305   ****Figure 5 about here****

306   Instability and storminess can result during periods when a number of climate driving

307   mechanisms interact (e.g. El Niño/Southern Oscillation, Indian Ocean Dipole and the

308   Southern Annular Mode) to influence the occurrence of regional weather systems such as east

309   coast lows and cut off lows (Pook et al. 2006, Verdon-Kidd and Kiem 2009). However, the

310   large-scale climate phenomena impact various regions of Australia at different times of the

311   year and to varying degrees, therefore it is not surprising that the timing of shifts in the

312   annual maxima timeseries varies spatially and temporally. This highlights the limitations of

313   trying to assess and attribute variability in annual maxima rainfall based on a single climate

314   driver (e.g. ENSO) or attempting to address the issue of climate trends for the whole of

315   Australia using one simple approach or model.

316   3.2   Effect of non-stationarity on IFD estimation

317   Section 3.1 provided evidence of non-stationarity in the annual maxima timeseries for a range

318   of durations. This non-stationarity may ultimately influence the IFD estimation depending on

319   the length of data, and the time period it comes from, and therefore the underlying climatic

320   state (or combination of states). Current IFD estimates for Australia (both the 1987 and 2013

321   versions) are based on data as short as 30 years for the daily-read stations and 8 years for the

322   sub-daily data. Therefore IFD estimates based on relatively short-term data sets may under-

323   or over-estimate rainfall intensities, depending on where the data series fits within the long

324   term context (i.e. before or after a shift in annual maxima).

325   For many east coast stations a shift in 1-day annual maxima (along with the 7-day) occurred

326   around the 1940s - 1950s and again in the 1970s. This timing also corresponds to well-known

327   periods of change in the IPO (see Section 2.1.2 for a description of the IPO and its

328   influences). Therefore, to further explore the issue of regime shifts, breakpoints in the IPO

329   were used to stratify the annual maxima rainfall timeseries into IPO positive and negative

330   epochs for the three long sub-daily data sets described in Section 2.1.1 (i.e. Brisbane, Sydney

331   and Melbourne, see Figure 1a for location). The reason for selection of these stations was

332   twofold. Firstly, for all three stations, a shift in the annual maxima timeseries (for 1-day and

333 7-day) was observed during the 1940s and again in the 1970s, and secondly the stations

334 contain long records of pluviograph data (the shortest being from 1913 onwards). Figure 6a

335 shows the modulating effect of the IPO on total annual rainfall for the three east coast

336 stations. Annual maxima at the three east coast stations during the two IPO epochs are also

337 shown in Figure 6 (b-d) for event durations of 30 minutes to 72 hours (durations that are

338 critical for flood design applications). A two-sample Kolmogorov-Smirnov (KS) test was

339 applied to determine if the observed differences between the IPO positive and negative

340 rainfall distributions are statistically significant. Here the null hypothesis is that the two

341 samples are drawn from the same distribution.

342 ****Figure 6 about here****

343 It is evident from Figure 6a that the effect of the IPO on annual rainfall totals (as measured by

344 the largest difference between the two rainfall distributions associated with each climate

345 phase and the results of the KS test) is greatest for Sydney. Although there does appear to be

346 some impact in Brisbane, the result was not statistically significant according to the KS test.

347 Melbourne does not appear to be greatly influenced by the IPO in terms of annual rainfall

348 variability. This is due to the fact that the southern regions of Australia are affected by other

349 climate modes than those arising from the Pacific (i.e. the Southern Annular Mode and the

350 Indian Ocean Dipole (e.g. Kiem and Verdon-Kidd 2010, Gallant et al, 2012)). Regions such

351 as Brisbane and Sydney tend to be dominated by Pacific Ocean influences (e.g. Verdon et al.

352 2004). Figure 6b shows annual maxima rainfall tends to be higher during IPO negative on

353 average for durations 6 hours and longer at Brisbane (though not statistically significant

354 according to the KS test), while Figure 6c confirms the same to be true for Sydney for

355 durations 2 hours and longer (statistically significant at 95%). However, for Sydney, the

356 outliers (represented by circles) tend to be larger during IPO positive, indicating that the less

357 frequent events might be more intense during this phase.

358   Irrespective of the fact that the annual rainfall totals for Melbourne do not show any

359   significant difference between the two phases of the IPO, there does appear to be a consistent

360   relationship between IPO and the sub-daily and daily statistics (Figure 6d), whereby the

361   median of the IPO positive distribution is higher across all durations, however IPO negative

362   is associated with less frequent but more extreme events (although results were not

363   statistically significant based on the KS test). For events 24 hours and longer, the IPO

364   negative distribution also shows a much higher degree of variability than smaller durations,

365   with the 'box and whiskers' extending beyond the IPO positive counterpart for these longer

366   durations. This suggests that while IPO might not be as dominant in southeastern Australia as

367   it is further to the north it still has some influence that needs to be better understood.

368   Based on the analysis presented in Figure 6 and the results of the KS test, the Sydney record

369   was chosen to further investigate the effects of regime shifts on IFD estimation. IFD

370   information was generated for the Sydney record using rainfall data from the two IPO phases

371   and the methodology outlined in Section 2.1 for durations 6 minutes through to 72 hours and

372   ARI 2 years to 200 years. In order to test the robustness of the point estimates of rainfall

373   return levels and estimate the uncertainty in their calculation, a simple bootstrap procedure

374   was carried out. Firstly the IPO positive and IPO negative rainfall timeseries were resampled

375   with replacement to obtain two new B-samples. Then for each B-sample the log-Pearson III

376   distribution was fitted and the rainfall intensities calculated for the various return intervals.

377   The difference between the rainfall intensities (of the two B-samples) was then calculated.

378   This procedure was repeated 100 times to build the empirical distribution of the differences

379   (which represents the effects of sampling and parameter estimation uncertainties under the

380   hypothesis of the existence of two different regimes).

381   Figure 7 shows the difference in rainfall intensity between IPO positive and IPO negative

382   estimates, along with the 95% confidence intervals (CIs) derived using the procedure above.

383   ****Figure 7 about here****

384   Figure 7 demonstrates clear differences in the resulting rainfall intensities for Sydney

385   estimated for each duration and ARI using the two regimes (i.e. rainfall data from either IPO

386   negative or IPO positive). The difference in rainfall intensity estimated is as great as 65% in

387   some cases.. In all cases, the magnitude of the difference in rainfall intensity estimated using

388   the different data regimes is greater for less frequent events (e.g. 50-year, 100-year, 200-year

389   ARIs), highlighting that uncertainty is greatest with less frequent events. The rainfall

390   intensity is greater in IPO positive for the very short duration events (6 minutes) at all return

391   intervals and for 30min duration events for return intervals of 10 years or more. Similarly, for

392   the 24 and 72 hour duration events rainfall intensity in the positive IPO phase is higher for

393   return intervals of 5 years or more. For 2 hour and 6 hour events, the negative phase results in

394   higher intensity events for more frequent return levels (20 years or less) but lower intensities

395   for less frequent events (50 years or more).

396   **4. Discussion and conclusions**

397   An analysis of regime shifts in the annual maxima timeseries (1-hour, 1-day and 7-day) has

398   been carried out using a set of high quality rainfall stations across Australia. It was found that

399   the annual maxima timeseries does indeed exhibit statistically significant step changes/shifts

400   for the majority of stations for various durations. Further it was demonstrated using three

401   long term sub-daily rainfall stations along the east coast that this impacts upon the resulting

402   IFD estimation. The potential for Pacific Influences (i.e. the IPO) to influence the resulting

403   IFD estimation was explored in order to demonstrate this issue. The authors acknowledge that

404   the IPO is unlikely to be the only driver of variability in the annual maxima timeseries across

405   Australia, and it is recommended that future research should aim to identify other potential

406   drivers of this variability.

407   These findings highlight the fact that in some instances the IFD estimates currently being

408   used are likely to be either under- or over-estimated at any one time depending on the length

409   of data, and climatic state, from which they were derived. This is a particular concern given

410   that current regionalised IFD information is based on data of varying length (as short as 8

411   year in the case of sub-daily data) spanning different time periods. An over estimation of

412   rainfall intensity for a given duration could impact on construction costs, while the risks of

413   underestimating rainfall intensities could result in failure of design criteria. That is, the risk is

414   dependent on the application and length of time over which the risk is assessed.

415   Further revisions of AR&R are currently underway to include an assessment of the potential

416   impacts of climate change on IFD estimates. However, there are many uncertainties

417   associated with climate change projections, particularly when extracting information on

418   timescales shorter than a season and particularly for hydrological extremes (e.g. Blöschl and

419   Montanari 2010, Kiem and Verdon-Kidd 2011, Koutsoyiannis et al. 2008, 2009, Montanari et

420   al. 2010, Randall et al. 2007, Stainforth et al. 2007, Stephens et al. 2012, Verdon-Kidd and

421   Kiem 2010). Therefore, assessing future changes in extreme events that occur over short

422   durations (e.g. minutes to days) is inherently difficult. Furthermore, climate projections are

423   presented in terms of a percent change from a particular baseline. However, the baseline is

424   often inconsistent and ill-defined leading to very different estimates of risk depending on the

425   time over which the baseline is calculated (as has been demonstrated in this paper).

426   Importantly, for regions where large-scale climate drivers operate on a multi-year to multi-

427   decadal timescales and are known to influence extreme rainfall events, we can use this

428   information to determine if the climate statistics on which the IFD are based are likely to be

429   biased or missing crucial information.

430   It is recommended that regime shifts in annual maxima rainfall be considered and

431   appropriately treated in any further updates of AR&R. One way to do this may be to only

432 utilise data sets of similar length ensuring that they span a sufficient number of years in order

433 to capture data from epochs of both high or low annual maxima (to remove bias towards one

434 climatic phase or another). However, it is acknowledged that this would potentially result in

435 discarding a large amount of data. alternatively, a separate set of IFDs could be developed for

436 use in high risk modelling for engineers who need to account for the 'worst case' (in a similar

437 manner to climate change allowances). This second set of IFD could be developed based on

438 the periods of elevated annual maxima alone (for those stations with clearly defined epochs

439 of annual maxima) such that if we were to enter such an epoch, designs based on these

440 estimates would be robust for the duration of such a period. Salas and Obeysekera (2014)

441 provide similar recommendations to deal with changing exceedence probabilities over time.

442 This would have to be assessed and calculated on a region by region basis given that

443 Australia is a country associated with high spatial and temporal rainfall variability caused by

444 numerous large-scale climate drivers and regional weather phenomena. Finally, any revised

445 estimates of annual maxima should be compared in terms of uncertainty bounds (e.g.

446 following Koutsoyiannis (2006)). Uncertainty analysis, which takes into account both the

447 data availability and variability within the observation period would provide relevant

448 information to practitioners about the reliability of IFD estimates.

449   This study has highlighted the existence of regime shifts in annual maxima rainfall data in

450 Australia. The driving mechanisms of these regime shifts are likely to vary from location to

451 location and decade to decade. However, these shifts are typical of many natural phenomena

452 and can be described by processes characterized by long range dependence (or regime-

453 switching processes) and captured by hidden Markov models (or similar), resulting in a

454 mixture of distributions that alternate stochastically according to the transition probability

455 from one regime to the next (e.g. Serinaldi and Kilsby, 2015a). While the strategy of defining

456 IFDs for two (or more) different regimes (e.g Serinaldi and Kilsby (2015a)) currently only

457 partially solves the problem, as we often do not know the beginning or the end of a specific

458 regime (be it rainfall or climate driver), recent work has focused on optimizing designs and

459 planning strategies based on the range of what is plausible rather than a reliance on knowing

460 the current and future climate state (e.g. Mortazavi-Naeini et al., 2015). At the same time,

461 work is also underway on seamless prediction at a range of timescales and if/when this

462 eventuates the results discussed here become even more important/useful. Nevertheless, the

463 immediate usefulness of the insights presented here occurs when first establishing the IFD, as

464 an approach similar to that employed here can be used to determine if the underlying data are

465 biased to a mostly wet or mostly dry regime (or a mix of both) which then provides an

466 indication as to whether the IFD is likely to be an over- or underestimate of the true risk.

467 Importantly, this issue needs to be considered and accounted for when attempting to estimate

468 IFD design rainfalls and prior to quantifying how those IFD estimates might change in both

469 the near and long-term future.

470 While the analysis presented here has been conducted using rainfall data from Australia

471 alone, the recommendations provided are likely to be applicable for other regions of the

472 world where IFD information is based on short term records and particularly for locations

473 with a highly variable climate.

5. Acknowledgements

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613

614   FIGURES

615
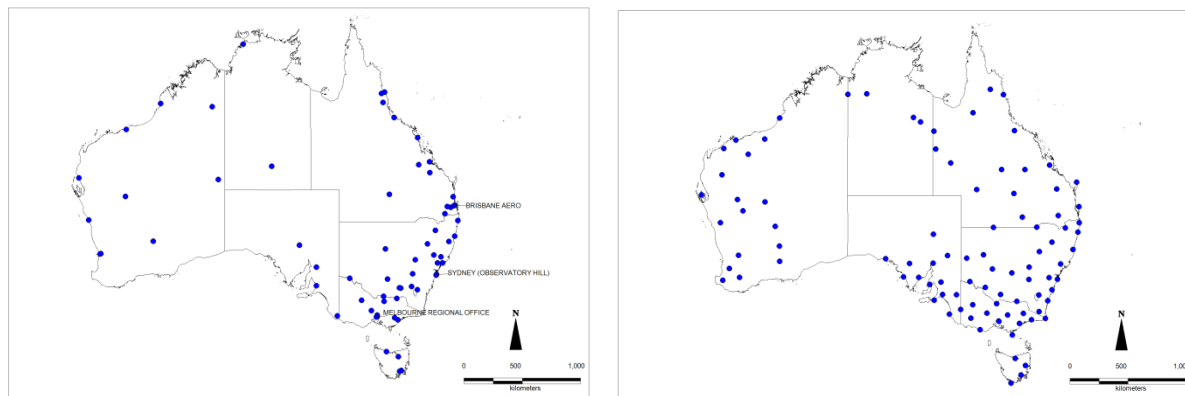
a)   b)

616   Figure 1 a) Reference stations for sub-daily stations, b) Reference stations for daily rainfall.

617   Note the three long term sub-daily stations used in the IFD analysis are also labelled.
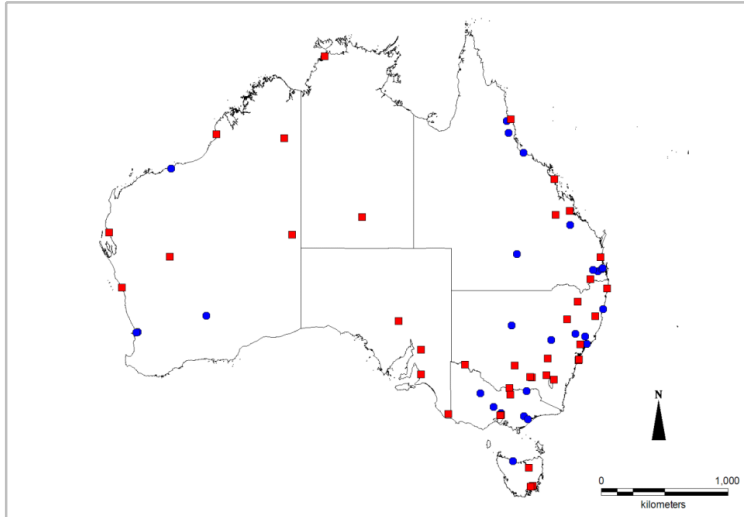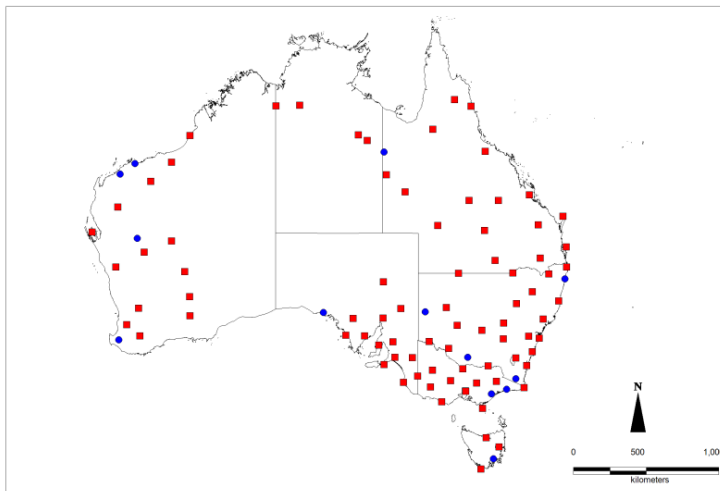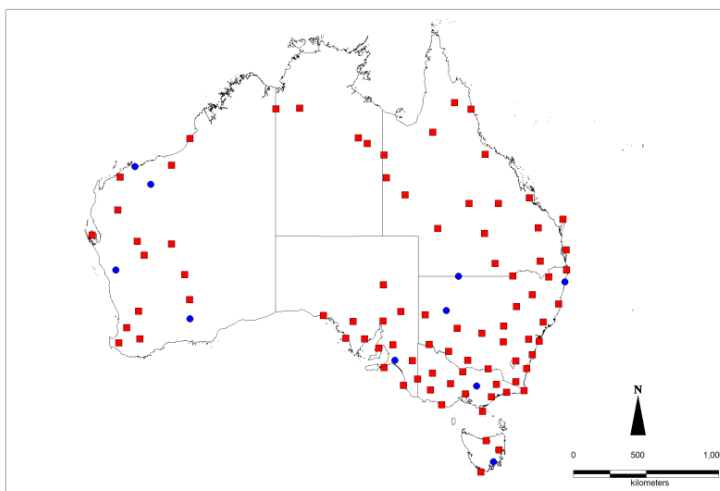
618   Figure 2 Stations (in red) with at least one statistically significant step change in the a) 1-

619   hour, b) 1-day, c) 7-day annual maximum rainfall (using the Mann-Whitney U test)

a)

b)
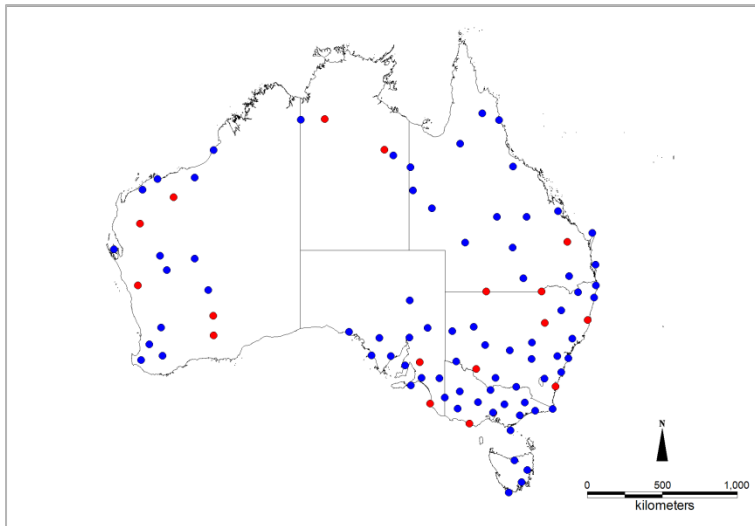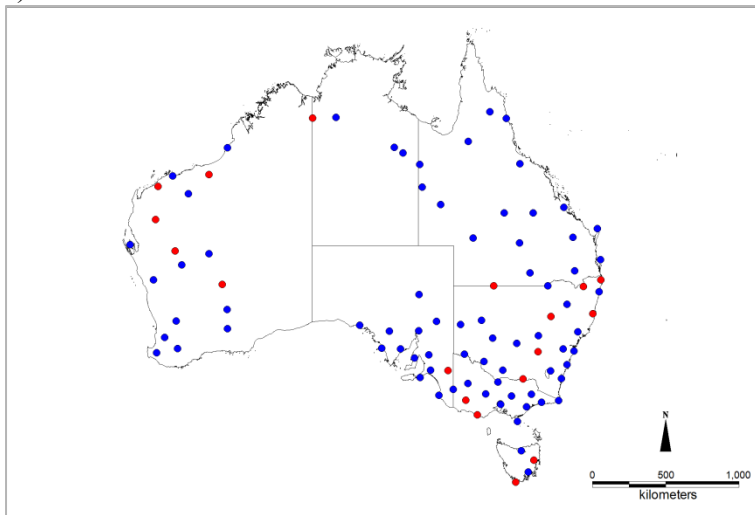
620   Figure 3 Stations (in red) with at least one statistically significant step change in a) the 1-day

621   and b) 7-day annual maximum rainfall (using the CUSUM test with resampling)

622

Conargo PO 7-day annual maximum rainfall
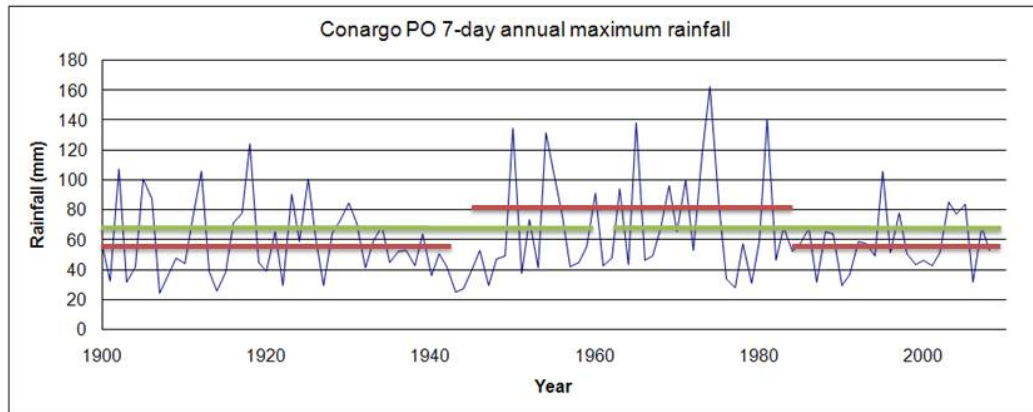
623

624 Figure 4 Example of inadequate identification of non-stationarity using CUSUM test (red line

625 highlights three distinct epochs of high/low rainfall, while green line demonstrates effect of

626 splitting the data into two sections for CUSUM test)

627

a)

b)

c)
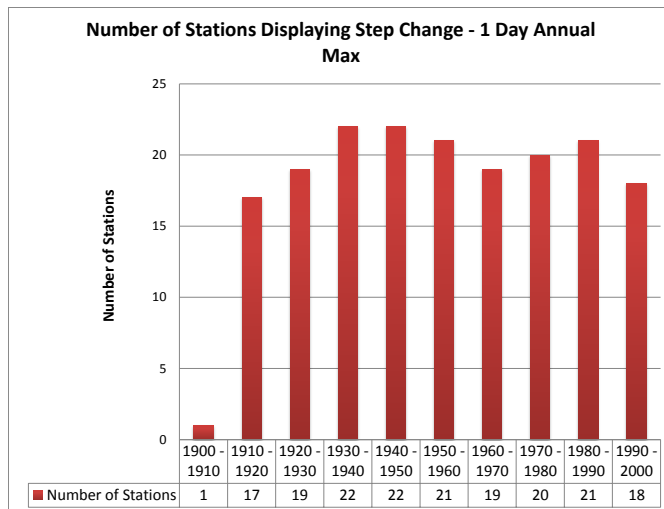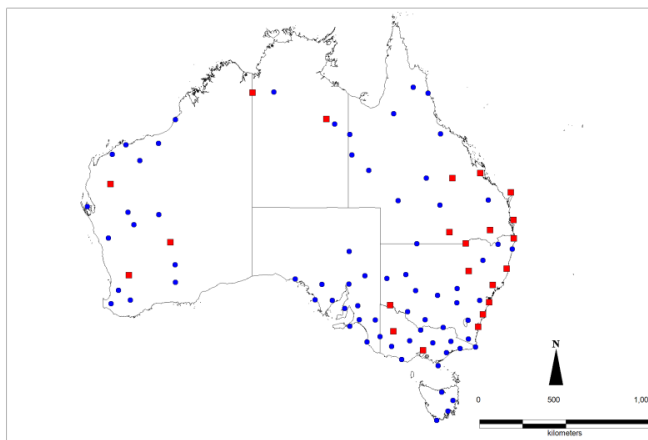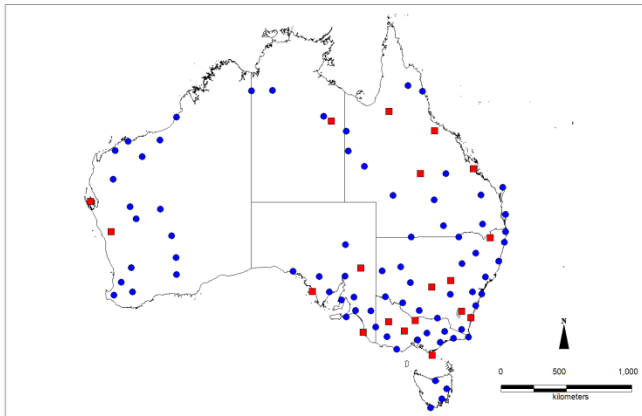
628 Figure 5 a) number of stations each decade displaying evidence of a step change in 1-day

629 annual max, b) Stations (in red) with at least one statistically significant step change in the 1-

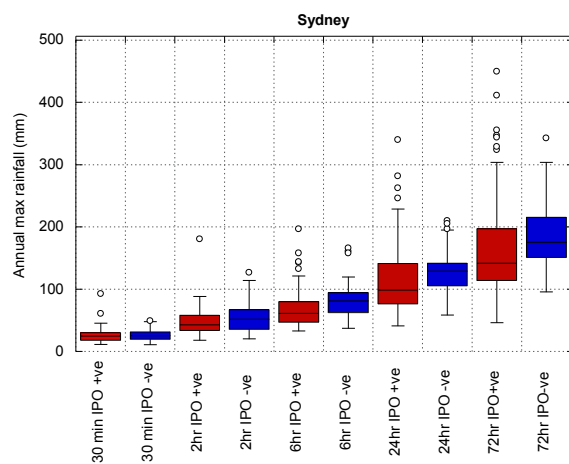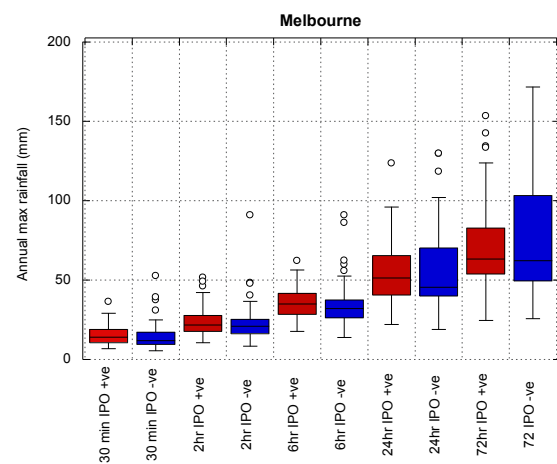630 day annual max during 1940-1950 (using the Mann-Whitney U test), c) Stations (in red) with

631 at least one statistically significant step change in the 1-day annual max during 1970-1980
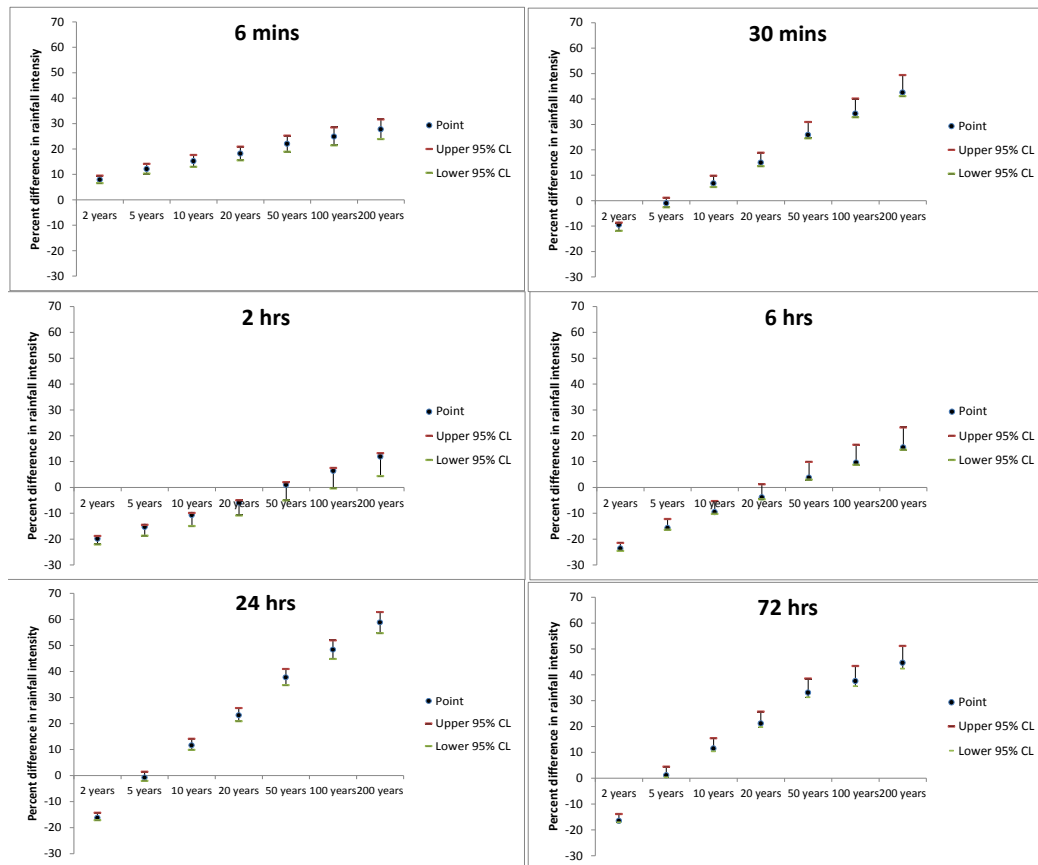
632 (using the Mann-Whitney U test)
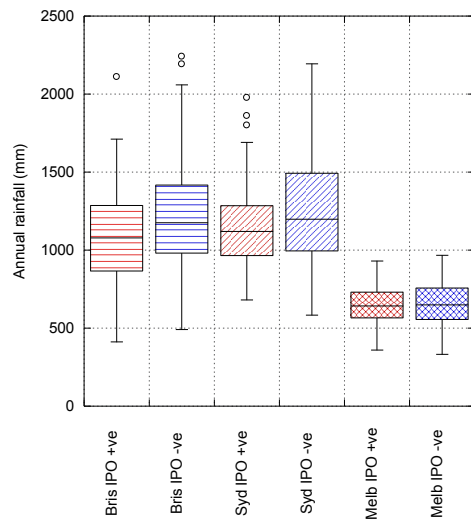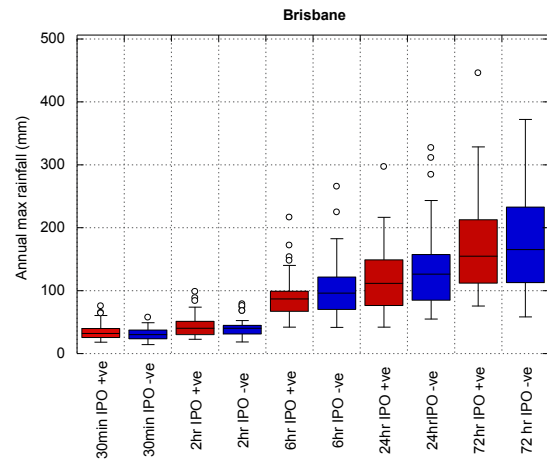
633   Figure 6 Relationship between IPO and a) total annual rainfall, and annual maximum rainfall

634   at various durations for b) Brisbane, c) Sydney and d) Melbourne.

635

636

Figure 7 Difference in rainfall intensity for each duration and ARI. Positive (negative) values represent an increase (decrease) in rainfall intensity during IPO positive compared to IPO negative