

Australian Rainfall & Runoff

Revision Projects

PROJECT 4

Continuous Rainfall Sequences at a Point

STAGE 1 REPORT

P4/S1/002

FEBRURARY 2010

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AUSTRALIAN RAINFALL AND RUNOFF
REVISION PROJECT 4: CONTINUOUS RAINFALL SEQUENCES AT A POINT

STAGE 1 REPORT

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FOREWORD

AR&R Revision Process

Since its first publication in 1958, Australian Rainfall and Runoff (AR&R) has remained one of the most influential and widely used guidelines published by Engineers Australia (EA). The current edition, published in 1987, retained the same level of national and international acclaim as its predecessors.

With nationwide applicability, balancing the varied climates of Australia, the information and the approaches presented in Australian Rainfall and Runoff are essential for policy decisions and projects involving:

- infrastructure such as roads, rail, airports, bridges, dams, stormwater and sewer systems;
- town planning;
- mining;
- developing flood management plans for urban and rural communities;
- flood warnings and flood emergency management;
- operation of regulated river systems; and
- estimation of extreme flood levels.

However, many of the practices recommended in the 1987 edition of AR&R are now becoming outdated, no longer representing the accepted views of professionals, both in terms of technique and approach to water management. This fact, coupled with greater understanding of climate and climatic influences makes the securing of current and complete rainfall and streamflow data and expansion of focus from flood events to the full spectrum of flows and rainfall events, crucial to maintaining an adequate knowledge of the processes that govern Australian rainfall and streamflow in the broadest sense, allowing better management, policy and planning decisions to be made.

One of the major responsibilities of the National Committee on Water Engineering of Engineers Australia is the periodic revision of AR&R. A recent and significant development has been that the revision of AR&R has been identified as a priority in the Council of Australian Governments endorsed National Adaptation Framework for Climate Change.

The Federal Department of Climate Change announced in June 2008 $2 million of funding to assist in updating Australian Rainfall and Runoff (AR&R). The update will be completed in three stages over four years with current funding for the first stage. Further funding is still required for Stages 2 and 3. Twenty one revision projects will be undertaken with the aim of filling knowledge gaps. The 21 projects are to be undertaken over four years with ten projects commencing in Stage 1. The outcomes of the projects will assist the AR&R editorial team compiling and writing of the chapters of AR&R. Steering and Technical Committees have been established to assist the AR&R editorial team in guiding the projects to achieve desired outcomes.

Project 4: Continuous Rainfall Sequences at a Point

Although the concept of continuous simulation and the various techniques for development of alternative rainfall sequences have been discussed in the literature, validation of the total system has not been attempted and is the focus of this project. Furthermore, the intent is that a comparison of techniques will cover the complete range of storm and burst durations that are of interest for flood flow prediction. Previous studies have considered only a subset of these durations.

The aim of Project 4 is to validate the use of continuous rainfall sequences for estimation of flood flows with a desired frequency. To achieve this primary aim, it will be necessary to:

- Compare predictions arising from alternative approaches to estimation of continuous rainfall sequences (these alternatives will include historical, transition probability matrix methods, nonparametric methods, and Disaggregated Rectangular Intensity Pulse models); and
- Compare flow predictions from simulations using the alternative predictions with recorded flow predictions.

Mark Babister
Chair National Committee on Water Engineering

Dr James Ball
AR&R Editor

AR&R REVISION PROJECTS

The 21 AR&R revision projects are listed below :

ARR Project No.	Project Title	Starting Stage
1	Development of intensity-frequency-duration information across Australia	1
2	Spatial patterns of rainfall	2
3	Temporal pattern of rainfall	2
4	Continuous rainfall sequences at a point	1
5	Regional flood methods	1
6	Loss models for catchment simulation	2
7	Baseflow for catchment simulation	1
8	Use of continuous simulation for design flow determination	2
9	Urban drainage system hydraulics	1
10	Appropriate safety criteria for people	1
11	Blockage of hydraulic structures	1
12	Selection of an approach	2
13	Rational Method developments	1
14	Large to extreme floods in urban areas	3
15	Two-dimensional (2D) modelling in urban areas.	1
16	Storm patterns for use in design events	2
17	Channel loss models	2
18	Interaction of coastal processes and severe weather events	1
19	Selection of climate change boundary conditions	3
20	Risk assessment and design life	2
21	IT Delivery and Communication Strategies	2

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BACKGROUND

The traditional approach to design flood estimation entails the specification of a design storm with a subsequent conversion to a design hydrograph and flood using a rainfall-runoff model. Such an approach assumes that (a) catchment initial conditions are not related to the magnitude of the design storm or flood being modelled, and (b) the exceedance probability associated with the design storm can be assumed to also be consistent with the resulting design flood. These assumptions are both questionable, with a design flood approach based on the use of continuous rainfall sequences having the potential to address each of these limitations.

The objectives of this project are to develop, test and validate the procedures for generating continuous rainfall sequences at point locations in Australia, as well as suggesting modifications in existing methods to account for the impact of climate change. This project is to be implemented over three stages, with this report describing the outcomes of the first stage.

The focus of this report is on the identification of alternative models to be compared in subsequent stages, the establishment of validation guidelines against which the models are to be tested, and the provision of a detailed scoping of subsequent stages including a description of the work needed to incorporate the effect of climate change on the generated stochastic sequences. In developing these comparisons, it is noted that at present only the Disaggregated Rectangular Intensity Pulse (DRIP) model of Heneker *et al* (2001) is available to Australian practitioners for the generation of continuous rainfall sequences. An alternative known as the nonparametric method of fragments (MOF) approach developed by Sharma and Srikanthan (2006) recently has been shown to perform well compared to a range of alternatives (e.g. Pui *et al*, 2009), however it is presently limited to locations at which extended, high-quality continuous rainfall data is available. An important contribution of the work presented in this report is therefore the extension of the MOF approach to any location where extended daily data is available, significantly broadening its applicability and providing a basis for comparison with other methods in the subsequent stages of this project.

EXECUTIVE SUMMARY

Continuous simulation of rainfall sequences is becoming an increasingly important tool in design flood estimation, as it represents arguably the most rigorous technique available to represent the joint behaviour of flood-producing extreme rainfall events and the preceding antecedent conditions. To inform the forthcoming revision of Australian Rainfall and Runoff (ARR), the aims of this project are to develop, test and validate the procedures for continuous simulation, as well as suggesting modifications in existing methods to account for the impact of climate change.

This report describes the outcomes from the first of three project stages leading up to the ARR revision. The emphasis of this stage is on providing a detailed overview of the continuous rainfall dataset, a review of the structure and properties of a range of alternative continuous simulation models, as well as the scoping of future stages. The outcomes of each of these aspects are summarised below.

The Australian continuous rainfall dataset

A detailed review of the Australian continuous rainfall dataset was provided, focusing on continuous gauges with less than 15% of data missing during the period from 1970 to 2005, totalling about 167 gauges distributed throughout all the major climatic regions of Australia. Due to the large number of long daily rainfall records in Australia compared to sub-daily records, the emphasis of the analysis was on examining the conditional relationship between daily rainfall and a range of sub-daily attributes. Consistency in the conditional daily/sub-daily relationship would mean that the characteristics of sub-daily rainfall can be effectively regionalised, significantly extending the applicability of continuous simulation as the basis for flood estimation Australia-wide.

The sub-daily attributes that were considered were the 6-minute, 1-hour and 6-hour maximum rainfall intensity for each wet day, as well as the wet fraction for each wet day. A histogram-based statistic was developed in which the similarity in the empirical joint distribution between each attribute and daily rainfall amount at any two locations could be evaluated. This statistic was then computed for each pair of locations, and the deviation in empirical histograms were correlated against a range of metrics including the distance, the differences in latitude and longitude, the difference in distance from the coast and the difference in elevation between each pair of locations.

The outcome of the analysis was that the latitude was the only significant determinant of similarity between daily rainfall amount and each of the sub-daily attributes, with lower latitudes having a higher proportion of the daily rainfall occurring in short-duration rainfall bursts. In contrast, the absence of any significant influence of the distance to coast or the elevation was surprising, and suggests that although these features clearly influence daily occurrence and/or amounts statistics, sub-daily statistics conditional to a daily rainfall amount are relatively homogenous.

In addition to the scaling behaviour between daily and sub-daily rainfall, timing of daily rainfall minima and maxima, as represented by the diurnal cycle, constitutes an inherent property of sub-daily rainfall which cannot be resolved at daily and longer timescales, yet provides significant information on the nature of rainfall occurring at that location, including the relative contribution of stratiform and convective rainfall events to the daily total rainfall amount. To our knowledge this study provides the first detailed review of the Australian rainfall diurnal cycle using the continuous rainfall dataset.

The results confirm the presence of a diurnal cycle in Australian rainfall which is strikingly consistent across all locations. For example, in more than 80% of the stations analysed, the daily minimum in rainfall occurrence was found between 0900 and 1100, regardless of the season. The daily maximum in rainfall occurrence was found between 1800 and 0600, with the result again being consistent across seasons. Interestingly, significant differences could be found between coastal (<50km from the coast) and inland (>50 km from the coast) rainfall, with inland rainfall showing an occurrence maxima from 1800 to 2000, whereas the coastal rainfall showed a more diffuse night time maximum. Finally the average amplitude of daily maxima, defined as the daily frequency maxima divided by the daily frequency mean, was greatest for summer at 31% and lowest for winter at 17%.

The diurnal cycle of rainfall intensity was slightly different than the diurnal cycle of rainfall occurrences. The intensity minima occurred in the period from 2300 to 0900 and was lowest mostly shortly after sunrise, while the maxima occurred during the afternoon from around 1000 to 2000, peaking around 1600. The amplitude of the intensity statistics was again greatest during summer at 37% and lowest during winter at 18%. Finally the most prominent diurnal cycle was observed for the rainfall amount, being the multiplication of occurrence and intensity, with maximum amplitude ratio of 61% in summer and minimum of 24% in winter. This suggests that the diurnal cycle of occurrence and intensity are mutually reinforcing, even though the timing of the maxima and minima are somewhat different.

The amplitude of the diurnal cycle was also evaluated against latitude, with highest amplitude occurring for low latitude regions. The greatest difference in amplitude between latitudes occurred in spring, with the high latitudes having amplitudes much lower than 50% in almost all cases, while the low latitudes often exhibit amplitudes of 100% or more. This relationship was observed for occurrence, intensity and amounts. In contrast, no relationship in amplitude could be found with distance from coast or elevation, even though the *timing* of the maxima did show strong influences in the distance from the coast.

Continuous rainfall simulation

In this report, four conceptual approaches to continuous rainfall simulation are described which are designed to simulate the behaviour of historical rainfall variability at sub-daily and longer timescales. These methods include:

- Event-based models, such as the Disaggregated Rectangular Intensity Pulse (DRIP) model;
- Poisson cluster models, including the Bartlett-Lewis Rectangular Pulse and Neyman-Scott Rectangular Pulse family of models;
- Multi-scaling models, such as the canonical and microcanonical cascades family of models; and
- Nonparametric resampling models, such as the *k*-nearest neighbour method of

fragments (MOF) approach.

All of these models were developed specifically to represent sub-daily rainfall, and most have been the subject of several decades of extensive research and refinement.

The outcomes of a literature review of a range of studies show that the DRIP, Poisson cluster models and MOF are each capable of simulating most of the properties of rainfall at most timescales, including many Intensity-Frequency-Duration (IFD) characteristics necessary for the simulation of flood estimation. Nevertheless, each of the models have weaknesses which highlight that no single model structure is likely to accurately capture all the statistics of rainfall at all timescales, so that the determination of the appropriate model will need to be application-specific.

An important application of continuous rainfall simulation is the generation of synthetic continuous rainfall sequences at locations for which little or no continuous data is available. Such situations require regionalised versions of the continuous simulation models, with the DRIP, Poisson cluster models and MOF each having a regionalised version available or under development. As no studies have been conducted comparing these regionalised continuous simulation models for Australian rainfall, at present it is not possible to describe the relative strengths and weaknesses of these models for applications where extended continuous data is unavailable.

Future stages

The work described in this report comprises the first of three phases associated with the development, testing and validation of procedures for generating continuous rainfall sequences. As a result of this work, the following tasks are recommended as part of the remaining stages of this project:

- Comparison of the MOF with DRIP and/or a Poisson cluster model at the same 10 locations and using the same statistics as described in Frost *et al* (2004) together with statistics which describe the joint probability of antecedent rainfall (e.g. 1, 7, 30 and 90 day aggregate rainfall) and the design rainfall event;
- Finalisation of the regionalised version of the MOF. The first phase of this work, which is nearing completion, involves the regionalisation of the MOF to any location for which extended daily data is available. A proposed additional phase involves the regionalisation to any location in Australia, by also incorporating a scheme for resampling from nearby daily rainfall gauges;
- Comparison of the regionalised version of DRIP, the MOF and possibly a Poisson cluster model for all the major climate regions in Australia; and
- Identification of alternatives to allow modification of selected methods for continuous simulation, for a number future time horizons under a number of assumed greenhouse gas emission scenarios.

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1. Introduction

The synthetic simulation of continuous rainfall sequences is becoming an increasingly important tool in flood hydrology, as a means of capturing the full joint distribution of flood-producing wet spells and the associated antecedent conditions leading up to the event. The benefits of such an approach were described at length in Kuczera *et al* (2006), in which continuous simulation together with event joint probability methods based on Monte Carlo simulation were suggested as viable alternatives to the design storm approach, particularly for volume-sensitive systems where the role of antecedent moisture conditions is expected to be important.

The development of continuous simulation models has been an area of active research for many decades, with a wide range of models now available. The focus of the work described in this report is on those models which are capable of simulating rainfall at the sub-daily timescale, as rainfall variability at this timescale must be accurately preserved for flood estimation in most urban systems (e.g. Beecham and Chowdhury, 2009) as well as many rural systems. To this end, four conceptual approaches to continuous rainfall simulation have been identified which have demonstrated capabilities at simulating rainfall at both sub-daily and longer timescales. These include event-based models such as the Disaggregated Rectangular Intensity Pulse (DRIP) model of Heneker *et al* (2001), the Poisson cluster models including the Bartlett-Lewis Rectangular Pulse and Neyman-Scott Rectangular Pulse family of models (Eagleson, 1978; Rodriguez-Iturbe *et al*, 1984; 1987a,b; 1988), multi-scaling models such as the canonical and microcanonical cascades family of models (Schertzer and Lovejoy, 1987; Gupta and Waymire, 1993), and nonparametric resampling models such as the recently developed method of fragments (MOF; Sharma and Srikanthan, 2006).

There have been numerous studies evaluating the performance of each of the above continuous simulation approaches for locations where extended continuous data are available for calibration of the modelling parameters (e.g. Frost *et al,* 2004; Pui *et al*, 2009). Despite this, most modelling applications are likely to be at locations where extended continuous instrumental records are unavailable, such that some form of regionalisation becomes necessary. Research into regionalised versions of the above continuous simulation approaches is comparatively sparse and recent, although regionalised versions are now available for DRIP (Jennings *et al*, 2009) and the Poisson cluster models (e.g. Cowpertwait and O'Connell, 1997; Gyasi-Agyei, 1999; Gyasi-Agyei and Parvez Bin Mahbub, 2007).

An underlying assumption of any regionalised continuous simulation approach is that the properties of sub-daily rainfall can be transferred to the location of interest from one or more nearby locations where extended data is available, either unmodified or through an adjustment of model parameters based on aggregate (e.g. daily-scale) rainfall characteristics. The degree to which such regionalisation is possible across Australia therefore requires an analysis of the homogeneity of various sub-daily rainfall properties, with a significant focus of the work described here being to examine commonalities and differences in scaling behaviour from daily to sub-daily rainfall across Australia, as well as an exploration of the diurnal cycle which not only informs the timing of precipitation events throughout the day, but also can be viewed as an indicator of the type of rainfall (e.g. convective or stratiform) which dominates at the location of interest (Dai, 1999).

Due to the promising performance of the MOF model for locations with extended continuous data (e.g. Sharma and Srikanthan, 2006; Pui *et al*, 2009), the question of whether this model structure is also amenable to regionalisation is also worthy of consideration. To allow for regionalisation, it will be necessary to resample sub-daily rainfall fragments from nearby continuous rainfall stations conditional to at-site daily rainfall amount and previous- and next-day rainfall occurrence. A further contribution of this study is therefore to develop a procedure for the identification of 'similar' continuous rainfall stations across Australia which can be used in the conditional resampling.

The remainder of this report is structured as follows. In the next section, a detailed overview of the complete Australian continuous rainfall dataset is provided, including a discussion of data availability and record length, a description of the daily/sub-daily rainfall scaling behaviour, as well as a detailed description of the Australian precipitation diurnal cycle. In **Section 3**, a description is provided of the four main classes of continuous simulation models described above, including a discussion of conceptual strengths and weakness as well as the description of various empirical studies developed to test the models. Lastly, a detailed scoping of future stages is provided in the last section of this report, with a focus on the validation of alternative models identified here, as well as a more detailed examination of possible approaches for incorporating climate change into the continuous rainfall sequences.

2. The Australian continuous rainfall dataset

The Australian continuous rainfall dataset used in this analysis comprises 1397 stations obtained from the Australian Bureau of Meteorology (pers. coms. Sri Srikanthan) distributed throughout the country, in increments of 6 minutes. The location of each gauging station is shown in **Figure 1**, together with an indication of the length of record at each station.

As can be observed from this figure, of the 1397 available gauging stations, only 101 locations are of length greater than 40 years, and a further 331 locations are of length of between 20 and 40 years, highlighting the relative scarcity of long continuous rainfall records. The spatial distribution of the gauging stations also is not homogenous, with a high density of gauges in the populated regions along the eastern coastal fringe of Australia and lower density elsewhere. Nevertheless, extended (>40 yr) records are available in all capital cities and many other urban centres, and the coverage does include all the major climate regimes in Australia.

The number of gauging stations with continuous rainfall records is also plotted against the year of record in **Figure 2**. As can be seen, only a small number of gauging stations were available in the early 20th century (the longest record is available from Melbourne Regional Office, gauge number 086071, with data available from 1873 to 2008), with significant increases in recording density apparent in the 1960s. Unless otherwise indicated, subsequent analyses described in this report use only those stations with less than 15% of the record missing for the period from 1970 to 2005, to both maximise record length and the number of stations with concurrent records.

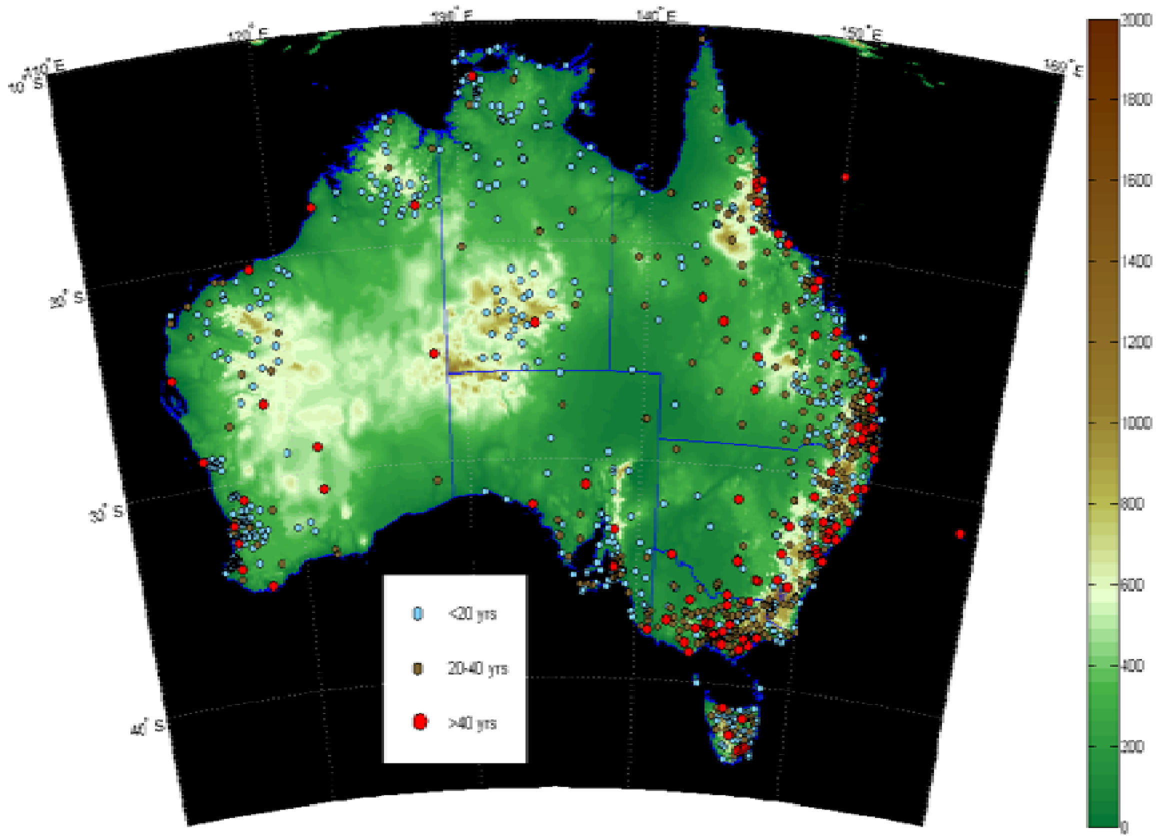

Figure 1: Spatial coverage and record length of the Australian continuous rainfall record.

In contrast to the continuous rainfall dataset, the Australian daily dataset comprises 17762 stations, of which 1375 provide more than 100 years of record (Leonard, 2009). The significant difference in data availability across Australia at daily and sub-daily timescales suggests that, for continuous simulation to be considered as a viable alternative to the design storm approach across Australia, sub-daily rainfall attributes will require some form of regionalisation. In the next section, the properties of various sub-daily rainfall attributes will be examined *conditional* to daily rainfall, to determine the degree to which such regionalisation is likely to be possible using the more widely available daily dataset.

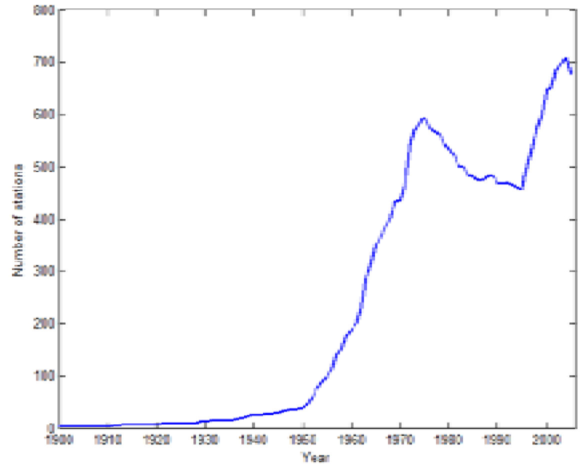

Figure 2: Number of Australia-wide continuous rainfall records against year of record.

2.1. Attributes of sub-daily rainfall

The variability in aggregate rainfall, such as at the seasonal or annual scale, from one location to the next is generally well understood. For example, coastal regions in Australia are typically wetter than regions further inland. Furthermore, whereas locations such as Sydney show only a limited seasonal cycle in total rainfall amounts, other locations such as those in tropical northern Australia show a pronounced summer wet season and winter dry season.

What is generally less well understood is the conditional behaviour of sub-daily to daily rainfall. For example, consider the case where we know the daily rainfall for a particular location on a given day was 50mm. How is this rainfall likely to be distributed throughout that day? Is it likely to occur as a single wet burst of 1 hour duration, or more evenly distributed as low intensity rainfall over the entire day? Importantly, if we had information on sub-daily rainfall characteristics at a nearby continuous rainfall gauge but only daily information at the location of interest, could the scaling behaviour between daily and sub-daily rainfall be used to represent sub-daily rainfall patterns at that location?

To address these questions we classified a wet day as one with more than 0.3mm rainfall (the results were insensitive to the precise definition of wet day), and then for each wet day calculated the following sub-daily rainfall attributes:

1) 6-minute maximum rainfall intensity;
2) 1-hour maximum rainfall intensity;
3) 6-hour maximum rainfall intensity; and
4) Fraction of day with no rainfall, estimated as the number of 6-minute intervals with no recorded rainfall divided by the total number of 6-minute increments (i.e. 240).

2.1.1. Preliminary example

The conditional behaviour of sub-daily to daily rainfall is illustrated for three locations in Australia: Hobart, Sydney and Darwin, for the months January, February and March. This is shown in **Figure 3**, with both daily and sub-daily rainfall plotted on a logarithmic scale. The 1:1 line in the joint probability plot represents the case where all the daily rainfall occurs within the maximum 6-minute rainfall burst, with all points in the plot necessarily falling on or to the right of this line. The 1-hour and 6-hour plots (not shown) behave similarly but are distributed closer to this 1:1 line, as clearly the maximum 6-hour burst contains a greater fraction of the day's rainfall than the 6-minute burst. A LOESS smoother is also applied to the data in **Figure 3** and represents a moving average at each location, and shows that the departure from the 1:1 line increases with increasing daily rainfall amount, suggesting that the proportion of the daily rainfall falling as the maximum short-duration burst is conditional to the total amount of rainfall for that day.

An interesting result is the differing characteristics of Hobart, Sydney and Darwin sub-daily rainfall attributes. Specifically, on average the 6-minute rainfall storm intensity for Darwin (red line) is much closer to the 1:1 line, while the average 6-minute storm intensity for Hobart is furthest from the 1:1 line, with the same conclusions derived for the 1-hour and 6-hour storm burst. This

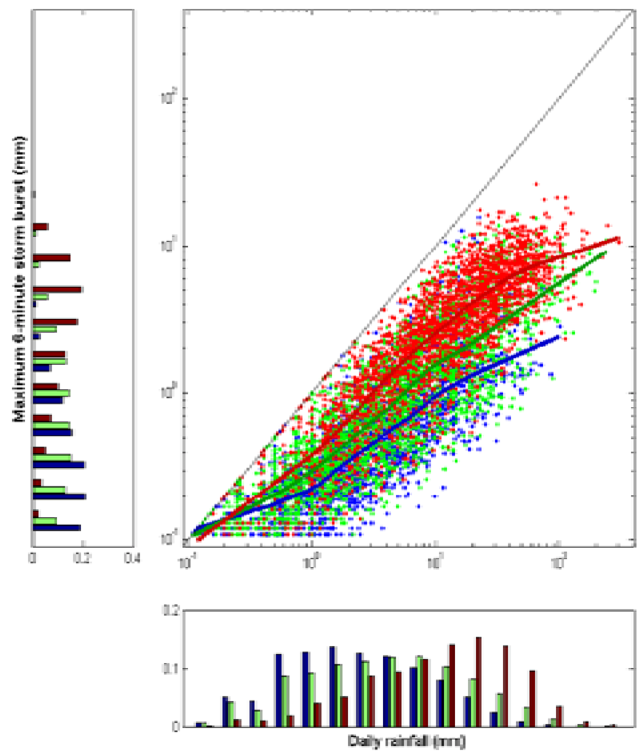

Figure 3: Maximum 6-minute storm burst against daily rainfall for each wet day, for Darwin (red), Sydney (green) and Hobart (blue), plotted on a logarithmic scale. Mean response estimated using a LOESS smoother fit to the log-transformed data. Plot includes marginal histogram of 6-minute (left panel) and daily (bottom panel) rainfall, and joint scatterplot (centre panel)

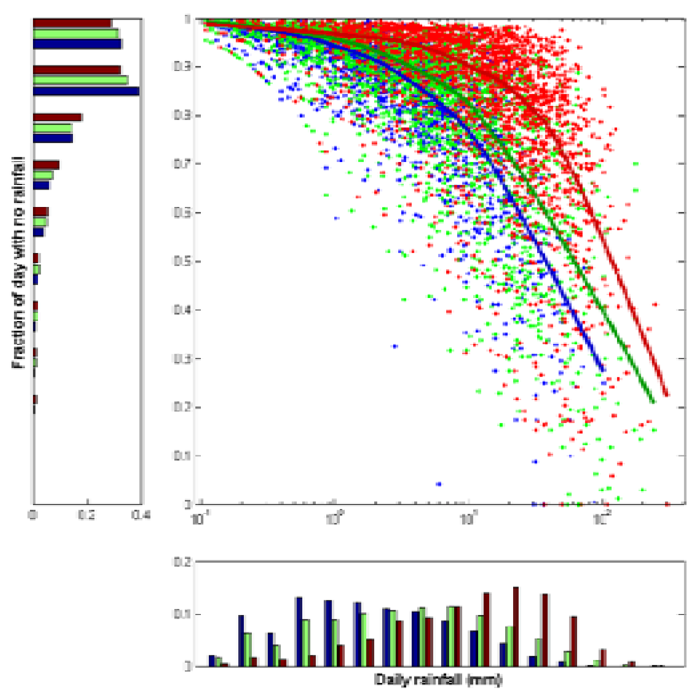

Figure 4: as for Figure 3, but with fraction of wet day with no rainfall plotted against daily rainfall amount.

suggests that in Darwin, a greater proportion of the daily rainfall falls as high-intensity short-duration storm bursts, while in Hobart the rainfall is more evenly spread throughout the day.

A similar conclusion can be obtained by considering the relationship between daily rainfall amount and fraction of day with no rainfall as presented in **Figure 4**. Here, for all daily rainfall amounts Darwin rainfall shows a greater proportion of the day as dry compared with the other locations, with the actual dry fraction being highly conditional to the daily rainfall amount.

2.1.2. Measuring similarity

Although the preceding example visually highlighted distinct differences between the daily/sub-daily relationships at three distinctly different locations, it is necessary to develop a metric that will allow for a quantitative comparison of the similarity between the daily/sub-daily attributes from a large number of continuous records, to determine under which conditions the continuous rainfall data at any two locations are likely to be 'similar', and therefore amenable for use in regionalisation.

A nonparametric statistic known as the Mean Integrated Squared Error (MISE; see Scott, 1992) was developed for this purpose, as it is able to provide a measure of the departure of the empirical joint probability density function of daily and sub-daily rainfall attributes at any two locations. The empirical joint probability density function for each daily/sub-daily attribute relationship is estimated using a histogram approach, in which the sample is divided into equally spaced bins (with spacing in the logarithmic scale for all attributes except for fraction of day with no rainfall), and the number of occurrences in each bin then being counted. The frequency histograms are transformed to density histograms by dividing each bin by the total number of data points in all bins, with the joint density histogram integrating to unity.

Letting v_k denote the bin count of the *k*th bin, then the empirical histogram for daily rainfall and any one of the sub-daily attributes listed above at any given location is defined as:

$$\hat{f} = \frac{v_k}{nh_xh_y} \qquad (1)$$

where h_x and h_y are the bin widths in the *x* and *y* dimensions, and *n* is the total number of data points. The MISE of the density histograms at two locations can then be calculated as the integration of the squared difference of each histogram bin:

$$MISE = E\left\{\int\left[\hat{f}_i - \hat{f}_j\right]^2 dx\right\} \qquad (2)$$

where the subscripts *i* and *j* refer to the two locations.

In all cases the histograms are constructed by pooling rainfall from three consecutive months. For example, the data in **Figures 3** and **4** were derived using data from Jan-Feb-Mar. This was done to maximise the number of data points (rain days) while simultaneously ensuring that seasonal effects did not unduly influence the results. Using data from 1970 to 2005, and assuming that about a third of the days in any given month are wet, the average number of histogram data points is about 1000. Based on this number, Sturges' number-of-bins rule suggests about 11 bins assuming a Gaussian distribution, with a slightly greater number recommended in the case of non-Gaussian distributions (Scott, 1992). We therefore selected a bin width for the joint distribution about double that used for the marginal distributions indicated in **Figures 3** and **4**.

The MISE was calculated for all two station pairs for each of the four sub-daily attributes listed in the previous section, with the final skill score derived as the averaged MISE across each of the four attributes and across all seasons.

2.1.3. Australia-wide analysis

The approach described above was applied to the full Australian continuous rainfall record between 1970 and 2005 for which less than 15% of the record is missing, totaling 167 locations Australia-wide or 13861 station pairs. In addition to calculating the MISE skill scores, the following factors were calculated for each station pair:

1) Distance metrics, including difference in total distance and the difference in latitude and longitude between stations;
2) Differences in elevation; and
3) Differences in the distance from the coast.

It is hypothesized that each of these factors could act as a predictor of whether the conditional daily/sub-daily relationship at any two stations is similar.

A regression model was developed in which each of the predictors was regressed against a log-transformed version of each of the MISE skill scores (i.e., 6-minute, 1-hour and 6-hour rainfall, and dry fraction), as well as the average MISE for all four attributes. The use of a log-transformation ensures that the regression residuals follow an approximately Gaussian distribution. The results using the MISE calculated for each sub-daily rainfall attribute were found to be similar, and as such only the results using the MISE averaged over all four attributes are presented.

The coefficient of determination obtained after regressing the average MISE against each of the factors presented above is shown in **Table 1**. Considering the distance metrics first, it is clear that the greatest coefficient of determination is for the differences in latitude between respective station pairs, whereas very little influence could be observed for changes in longitude. The absolute distance has a coefficient of determination greater than that for longitude and less than that for latitude, suggesting that it is the difference in latitude which provides the most significant driver for whether the daily/sub-daily fragments at two stations are similar.

Table 1: Log-transformed average MISE against a range of plausible predictors

Predictor	R^2
Distance between stations (km)	0.25
Difference in longitude	0.06
Difference in latitude	0.40

Difference in distance from coast (km)	0.04
Difference in elevation (m)	0.02

A plot of the MISE against difference in latitude is provided in **Figure 5**. Although there is clearly a lot of scatter, the general trend of increasing MISE with increasing difference in latitude is clear. The line of best fit (red line) was developed through linear regression against the log-transformed the MISE, and therefore is reasonably approximated as an exponential curve. The implications of such a curve are significant; the skill scores are relatively insensitive to small differences in latitude up to about 5° or 10°, whereas significant divergences in the daily/sub-daily characteristics are apparent for greater latitude differences such as those observed in the Hobart, Sydney and Darwin rainfall shown in **Figures 3** and **4**.

Finally, the results in **Table 1** suggest that both the difference in distance from coast and difference in elevation yield low coefficients of determination, with values of 0.04 and 0.02 respectively, suggesting that the daily/sub-daily rainfall relationship is relatively insensitive to these factors. This is not to say that daily rainfall does not change significantly as a result of changes in elevation or distance from the coast; rather, conditional to a given daily rainfall amount, the sub-daily attributes used in this analysis do not appear to be heavily influenced by these factors.

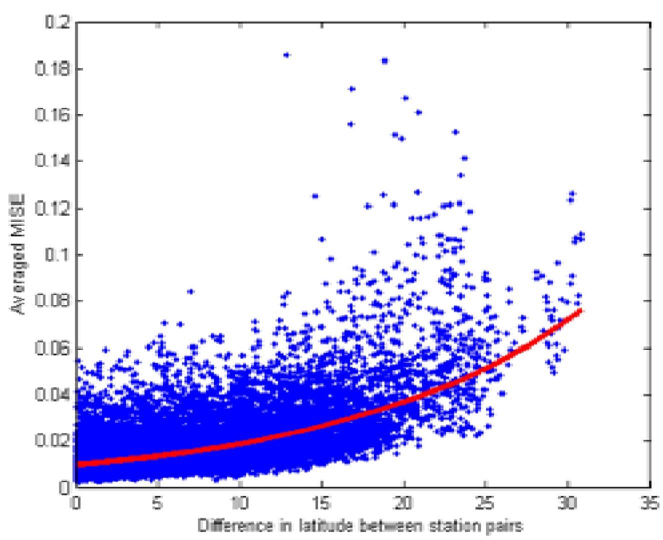

Figure 5: MISE averaged over all four sub-daily attributes for all station pairs, against difference in latitude between the station pairs (blue dots). Red line is the line of best fit after applying linear regression to log-transformed MISE.

The conclusion of this work is that latitude appears to be the primary determinant of the *scaling* between daily and sub-daily rainfall. This information is necessary in identifying nearby stations for regionalization of the nonparametric MOF approach developed by Sharma and Srikanthan (2006), and may also represent useful information for the regionalization of other daily to sub-daily disaggregation approaches. The general lack of sensitivity to latitude for small changes in latitude, and absence of sensitivity to other factors such as elevation and distance to coast, suggests that provided adequate daily data is available, significant regionalisation is likely to be possible using the finite continuous dataset presently available for Australia.

2.2. The diurnal cycle

An additional attribute of sub-daily rainfall which has received limited attention in the literature is the Australian rainfall diurnal cycle. This cycle represents an inherent property of sub-daily rainfall which cannot be resolved at daily and longer timescales, yet provides significant information on the nature of rainfall occurring at that location, including the relative contribution of stratiform and convective rainfall events to the daily total rainfall amount. The diurnal cycle may also significantly influence surface hydrology (e.g. evaporation, runoff), with rainfall in the afternoon likely to be evaporated more quickly than at night and thus potentially resulting in lower runoff. Finally, although not directly relevant to the work described in this report, an understanding of the diurnal cycle has been used to validate the performance of general circulation models (e.g. Dai, 2006), as correct simulation of the diurnal precipitation cycle is indicative of correct simulation of the underlying physics of precipitation formation.

To our knowledge this study provides the first detailed review of the diurnal cycle in Australian rainfall using the complete continuous rainfall dataset.

2.2.1. Review of previous work

Although only limited work has been conducted specific to Australian conditions, a number of studies have been completed at the global scale using a range of land- and satellite-derived datasets, and which can be used as a basis to compare the findings of the Australian diurnal cycle described later.

An important study of the global precipitation diurnal cycle used three-hourly weather reports from about 15000 stations around the globe (Dai, 2001) from 1975 to 1997, and found that over most land areas, drizzle and non-showery precipitation occurs most frequently in the morning around 0600 local solar time (LST), whereas showery precipitation and thunderstorms occur most frequently in the late afternoon. The proposed mechanism for this is a peak in atmospheric relative humidity (due to a trough in atmospheric temperature and an approximately constant specific humidity) contributing to an early-morning peak in low-intensity precipitation events, whereas solar heating on the ground produces a late-afternoon maximum in convective available potential energy (CAPE) in the atmosphere that favours late-afternoon moist convection and showery precipitation. Furthermore, when considering latitudinal variations in the diurnal cycle, it was found that in tropical regions for which convective precipitation represents the dominant precipitation inducing mechanism, the amplitude of the diurnal cycle is maximum, whereas in the high-latitude regions the diurnal cycle is weaker.

A more recent study using satellite-derived tropical precipitation data from the Tropical Rainfall Measuring Mission (TRMM) dataset (Kikuchi and Wang, 2008) from 1998-2006 identified three distinct diurnal cycle regimes – oceanic, continental and coastal – which were distinguished according to the amplitude, peak time and phase propagation of the cycle. Consistent with the study by Dai (2001), the continental regime features a large amplitude and an afternoon peak around 1500-1800 LST, whereas the landside coastal regime featured peaks from 1200-2100 LST. Although emphasising that a significant mechanism for the diurnal cycle is solar insolation, which thus explains the observed latitudinal and seasonal variability, the study acknowledges there remain significant uncertainties as to the exact mechanism of the diurnal cycle across continental and coastal regimes.

Finally, a notable study by Dai *et al* (1999) in the United States using a 31-yr hourly gridded precipitation product from approximately 2500 stations described in Higgins *et al* (1996) found significant interannual variability in the winter diurnal cycle, which was linked to the influence of the El Niño – Southern Oscillation (ENSO) phenomenon (Dai 1999), suggesting that the diurnal cycle, and the associated probability of convective and stratiform rainfall events, may not be stationary.

2.2.2. The Australian diurnal cycle

The diurnal cycle in Australian rainfall was examined using the historical record of continuous rainfall sequences from 1970 to 2005 described in **Section 2.1.3**. To ensure spurious results were not obtained due to small sample sizes, only those locations with more than 300 days rainfall in any given season were considered, so that locations such as southwest Western Australia during summer months and northern Australia during winter months were excluded from the analysis.

The methodology used to analyse the Australian point-location rainfall diurnal cycle was the same as was used by Dai (1999) to study the diurnal cycle of gridded rainfall in the United States, and is described as follows. The 6-minute increment continuous data was converted to hourly data, and all days with any missing data (indicated by either -8888 or -9999) were excluded from the analysis. Then for each hour of the day, the seasonal average frequency (percentage of hours having rainfall during the season), the average intensity for each rainfall occurrence (the rate when rainfall occurs and expressed as mm/hr), and the total rainfall amount (the product of the frequency, intensity and the number of days for the season) was calculated. The amplitude (defined as the difference between daily maximum and mean) and the phase (the local solar time or LST when the maximum occurs) from the seasonally averaged hourly data was then calculated.

An example of the diurnal cycle calculated for Sydney Observatory Hill (station number 066062) is shown in **Figure 6**. As can be seen, a distinct diurnal cycle is present for both frequency and rainfall amount, with a minimum occurring at 1000 and with a maximum occurring in the late evening around 2200. The intensity of rainfall shows similar timing of the minima and maxima, although there is significantly more scatter in the results.

To better understand the behaviour of the diurnal cycle across Australia, a vector plot of frequency minima is presented in **Figure 7** for summer rainfall, with the direction of the vector pointing to the LST at which the minima occurs, and the length of the vector representing the amplitude of the diurnal cycle. As can be seen, the similarity in terms of the timing of the minima across all the stations analysed is striking, with a histogram of the minima timing shown in **Figure 8** confirming that more than 80% of minima occur between the hours of 0900 and 1100 LST.

The histogram of frequency maxima is shown in **Figure 9** for the same summer months, and highlights a strong night time peak, with maxima occurring in the evening between about 1700 and 2300. The partitioning of data into coastal (<50km from coast) and inland (>50 km from coast) stations is shown in **Figure 10**, suggests that inland rainfall tends to occur in the early evening, whereas coastal rainfall is more evenly distributed throughout the night time and early morning.

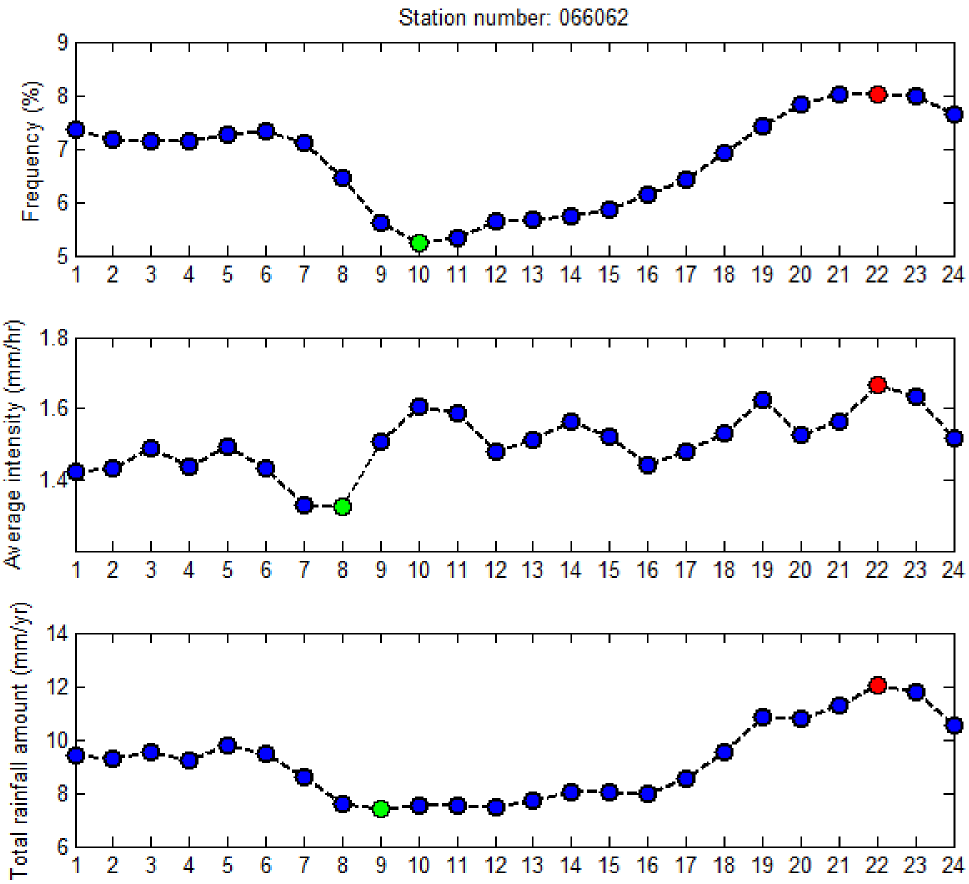

Figure 6: The diurnal cycle of frequency, average intensity and total rainfall amount plotted against time of day for Sydney Observatory Hill during the summer. The hourly data was smoothed using a three-point smoother, with the timing of the minima and maxima represented by green and red dots, respectively.

The diurnal cycle of rainfall intensity was also examined, and found to be slightly different than the diurnal cycle of rainfall frequency. Once again considering only summer rainfall, it can be seen in **Figure 11** that the intensity minima occur in the period from 2200 to 0900, while the maxima shown in **Figure 12** occur during the afternoon from around 1400 to 1900, peaking around 1600.

Finally, the diurnal cycle of rainfall amounts (not shown), which is the product of frequency and intensity, was found to be at its minimum at around 0900 and maximum around 1700, and corresponds to the average of the frequency and intensity histograms.

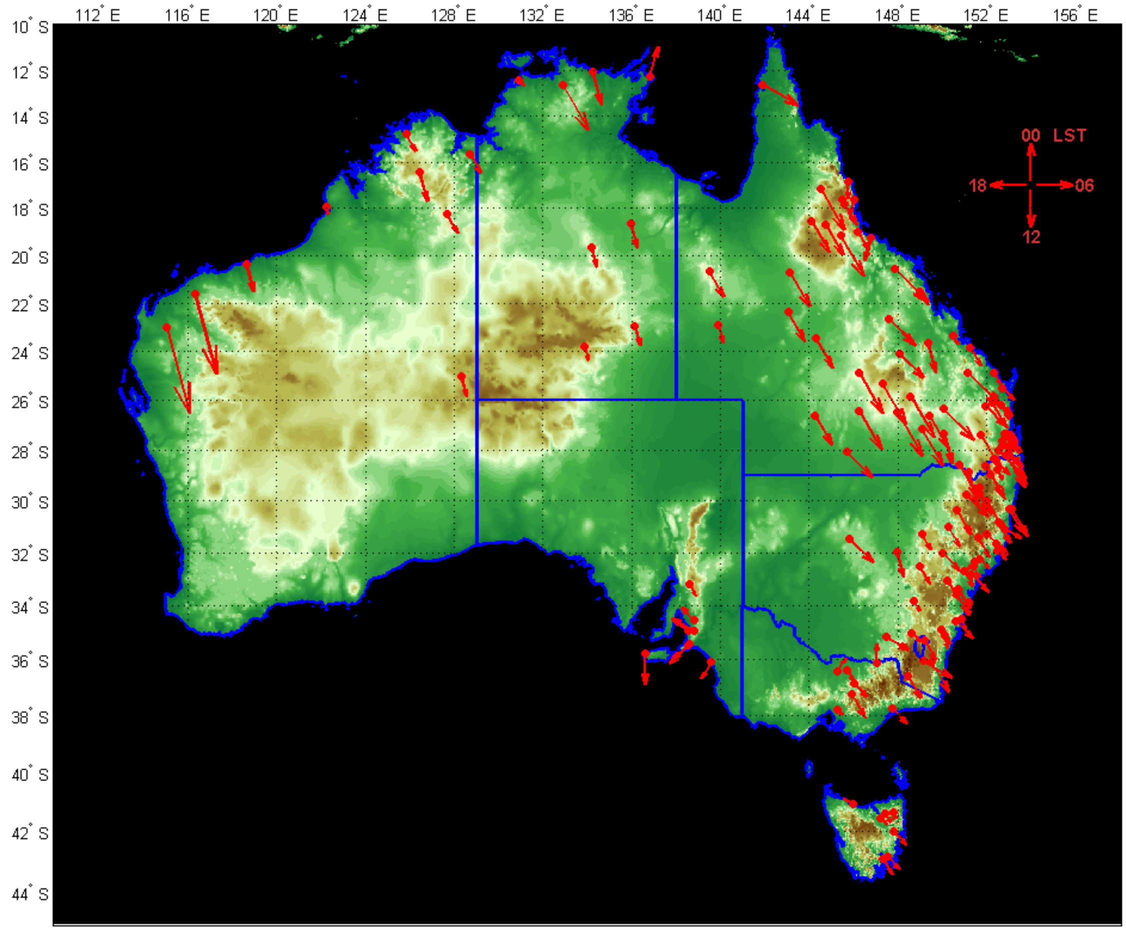

Figure 7: Vector plot of diurnal cycle of summer (DJF) rainfall frequency minima. The vector length represents normalised amplitude in percentage. The direction to which an arrow points denotes the local time at which the maximum amplitude occurs as denoted by the clock on the top right (north = 0000 Local Solar Time; east = 0600 LST; south = 1200 LST and west = 1800 LST). The length of the arrows on the clock corresponds to an amplitude of 50%.

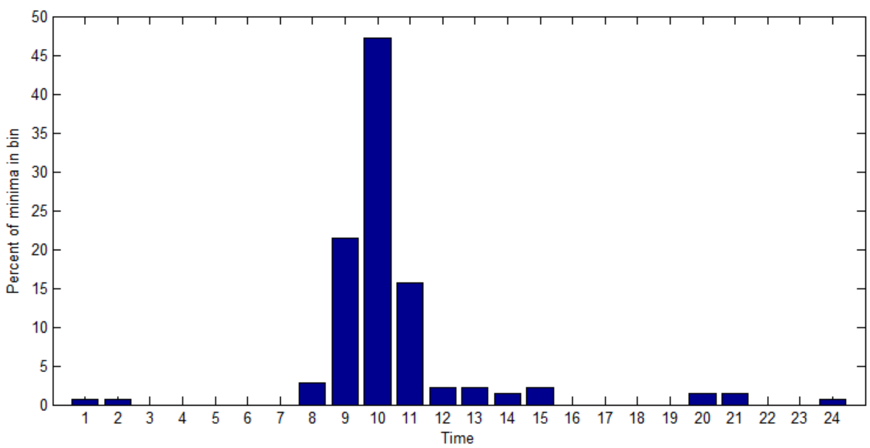

Figure 8: Percentage of stations with frequency minima against time of the day for summer.

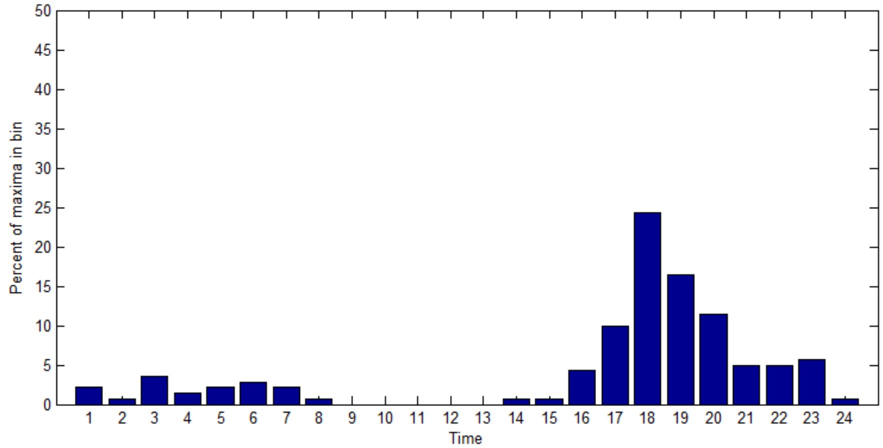

Figure 9: Percentage of stations with frequency maxima against time of the day for summer.

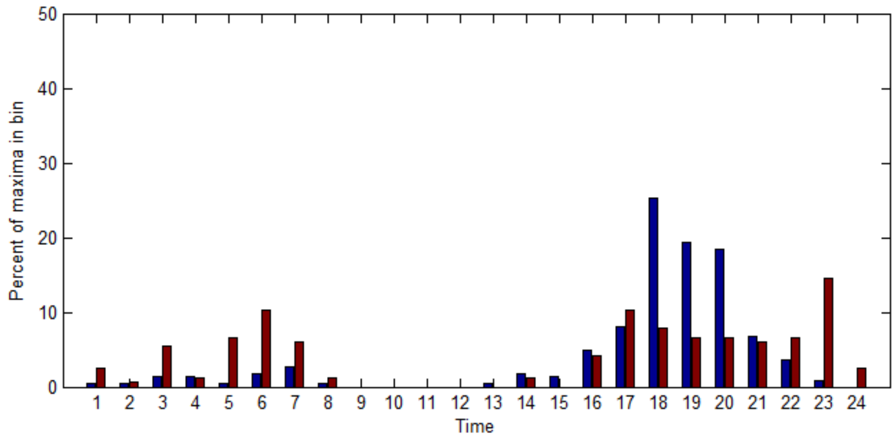

Figure 10: As with figure 8, but partitioned into inland (>50km from coast; blue) and coastal (<50km from coast; red).

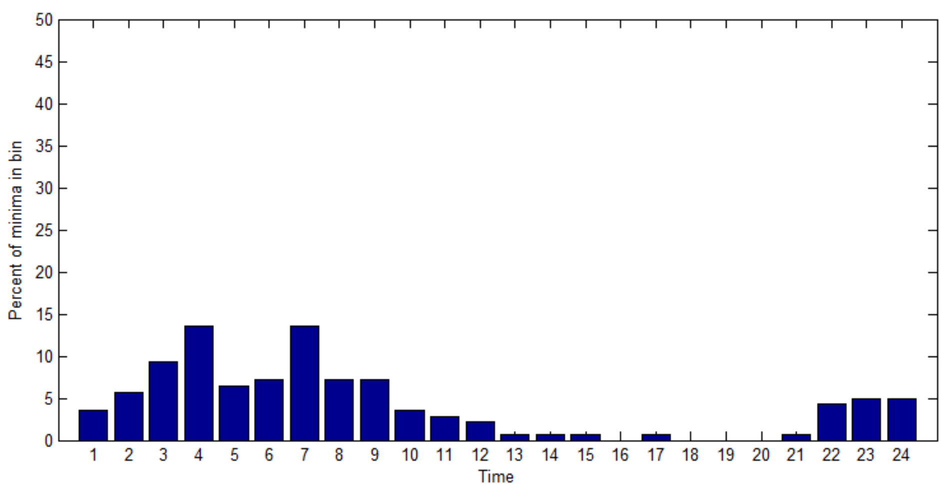

Figure 11: Percentage of stations with intensity minima against time of the day for summer

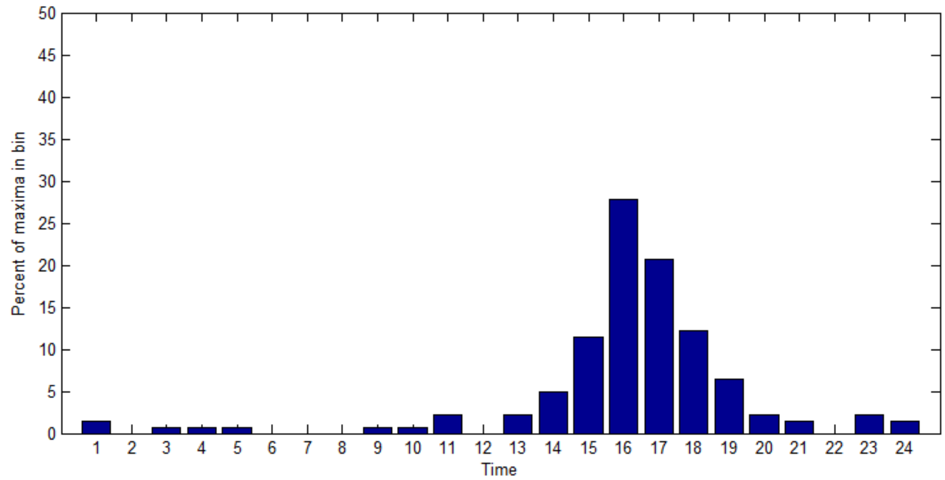

Figure 12: Percentage of stations with intensity maxima against time of the day for summer

The results for all seasons are summarised in **Table 2**, where it can be seen that the timing of the diurnal cycle is generally consistent across seasons. In contrast, the amplitude varies significantly on a seasonal basis. For example, the frequency of rainfall events has a maximum average amplitude of 31% during summer, and minimum amplitude of 17% during winter. The intensity results are similar, with maximum average amplitude of 37% in summer and minimum amplitude of 18% during winter. Finally, the most prominent diurnal cycle occurs for rainfall amounts, being the multiplication of occurrence and intensity, with maximum average amplitude of 61% in summer and minimum of 24% in winter. This suggests that the diurnal cycle of occurrence and intensity are mutually reinforcing, even though the timing of the maxima and minima are somewhat different.

To better understand drivers of this seasonal variability, a plot of frequency amplitude against latitude is shown in **Figure 13** for spring, and shows the amplitude ratio of the diurnal cycle increases from about 20% in the high latitude regions through to 50-170% in low latitudes. Similar relationships were also observed for rainfall intensity and amounts, suggesting maximum amplitudes of the diurnal cycle in tropical regions of Australia. Unsurprisingly, the latitudinal dependence was lower in winter due to decreased amplitude in the sub-tropical regions during this season, and also lower in summer due to increased amplitude in the higher latitude regions during this time.

In contrast, no relationship in amplitude could be found with distance to coast or elevation, even though as described earlier the *timing* of the maxima did show strong influences in the distance from the coast. These results are therefore consistent with the results described in the previous section on the scaling between daily and sub-daily rainfall, which highlight that as latitude decreases the proportion of high-intensity short-duration rainfall events (i.e. convective rainfall) increases as a fraction of total daily rainfall, with an absence of any relationship with distance to coast and station elevation.

Table 2: Summary of diurnal cycle results for each season, for frequency of rainfall occurrence, average intensity for each occurrence, and total rainfall amount.

Season	Number of stations	Frequency (%)			Intensity (mm/hr)			Amounts (mm/season)		
		Amplitude ratio (90%ile range)	**Time of minima** (80%ile range)	**Time of maxima** (80%ile range)	**Amplitude ratio** (90%ile range)	**Time of minima** (80%ile range)	**Time of maxima** (80%ile range)	**Amplitude ratio** (90%ile range)	**Time of minima** (80%ile range)	**Time of maxima** (80%ile range)
Summer	140	**31%** (13% - 65%)	**1000** (0900-1100)	**1800** (1700-2300)	**37%** (16% - 61%)	**0400** (2300-0900)	**1600** (1500-1800)	**61%** (23%-117%)	**0900** (0200-1200)	**1700** (1600-2000)
Autumn	124	**20%** (9% - 50%)	**1000** (0900-1100)	**1700** (1500-0700)	**24%** (11% - 52%)	**0700** (2300-0800)	**1600** (1000-1800)	**31%** (11%-92%)	**1000** (0100-1200)	**1700** (1500-2100)
Winter	111	**17%** (9% - 32%)	**1100** (1000-1100)	**0600** (1700-0600)	**18%** (10% - 36%)	**0700** (0100-0900)	**1100** (1000-2000)	**24%** (9% - 51%)	**1000** (0400-1500)	**1800** (1600-2300)
Spring	126	**27%** (13% - 52%)	**1100** (1000-1100)	**0600** (1600-0700)	**30%** (10% - 60%)	**0700** (0100-0900)	**1700** (1400-1900)	**52%** (17% -101%)	**0900** (0200-1100)	**1800** (1500-2000)

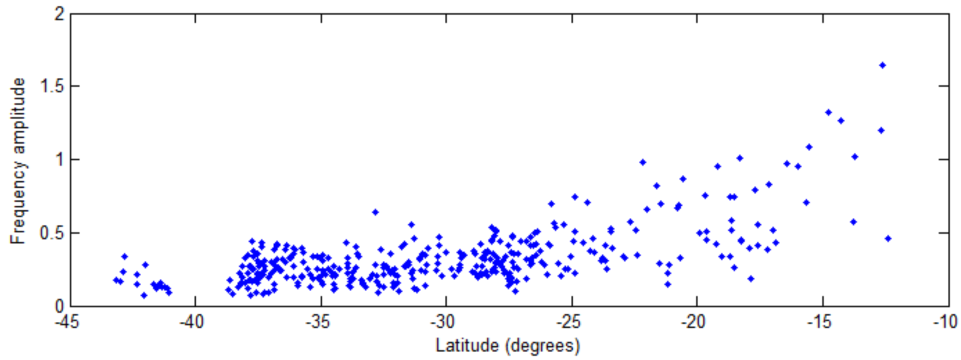

Figure 13: Frequency amplitude during spring. Results derived using a larger dataset (using all stations with <50% missing), and are qualitatively similar to the smaller dataset (<15% missing) used for the remainder of the analysis.

In conclusion, a pronounced diurnal cycle can be observed in Australian rainfall, with remarkable spatial homogeneity as well as strong consistency between seasons. The geographic and seasonal influences resulted in larger diurnal cycle amplitudes at low latitudes, and larger diurnal cycle amplitudes in summer compared with winter, with both likely to be due to an increased prevalence of convective rainfall systems occurring in the afternoon and early evening due to warmer temperatures and associated atmospheric instability (e.g. see discussion in Peppler and Lamb, 1989). Furthermore, a distinct coastal influence could be observed regarding the timing of the diurnal cycle maxima, with inland locations exhibiting a pronounced early evening maximum whereas coastal regions showed maxima distributed throughout the night time.

The implications of this analysis are several. Firstly, correct representation of the diurnal cycle in continuous rainfall simulation may result in better representation of runoff in cases where evaporative losses are expected to be important, with this expected to be most relevant for the reproduction of low flows. Secondly, the diurnal cycle is clearly related to rainfall-inducing mechanisms, which suggests that in regionalising the non-parametric MOF approach developed by Sharma and Srikanthan (2006), it will be necessary to select nearby stations with similar diurnal cycles, by, for example, only selecting stations at similar latitudes, and only selecting coastal stations if the location of interest is coastal.

Finally, the influence of inter-annual or inter-decadal variability in the diurnal cycle, or the identification of possible trends related to anthropogenic global warming resulting in possible changes in rainfall-inducing mechanisms described for the United States by Dai *et al* (1999) and Dai (1999), have not been considered here and represents an intriguing area of future research.

3. Continuous rainfall simulation

3.1. Overview

Continuous rainfall simulation refers to the synthetic generation of continuous rainfall sequences using one or more stochastic models, with the focus of this report being on those models that are capable of simulating rainfall at a single point location. It is noted that the main argument for the use of continuous simulation in design flood estimation is the elimination of the assumptions involved with the selection of initial and continuing losses and identification of a single temporal pattern for the design storm, such that the models described in this report are those which are able to reproduce sub-daily rainfall features, as well as the longer-term persistence characteristics which inform the antecedent moisture conditions of the catchment.

If extended, high-quality sub-daily rainfall data was available at any location of interest, the direct application the historical dataset to inform the rainfall-runoff modelling would in many cases be adequate for the purposes of flood estimation. Nevertheless, even for regions where significant sub-daily data is available, it should be remembered that the observed record represents only a single realisation of all possible rainfall sequences, such that the simulation of alternative sequences could be useful to better characterise flood quantiles at the point or in the system of interest.

As described earlier in this report, however, long and accurate pluviograph records are generally unavailable for most locations throughout Australia, although in many cases short-duration continuous rainfall data or extended daily data are available. This suggests that the greatest need for the generation of physically realistic, synthetic rainfall sequences most likely will be at locations where the instrumental record is at its most limited, with the hierarchy of data availability and associated assumptions described in **Table 3**.

Table 3: Hierarchy of assumptions associated with continuous rainfall simulation.

Data availability	Applicability of continuous rainfall simulation	Hierarchy of assumptions and sources of uncertainty[1]
Extended, high-quality pluviograph data	Low to medium, as continuous rainfall sequences and associated statistics (e.g. IFD statistics) often can be derived directly from the historical record. Nevertheless, as the historical data represents only a single realisation of all possible rainfall sequences, generation of alternative sequences could assist in better characterising flood quantiles at the point or system of interest.	Statistics of climate implied by the instrumental record valid for future period of interest.
Limited pluviograph data, and extended daily data	Medium, as recorded pluviograph data is insufficient to capture rainfall extremes or a sufficient	Scaling behaviour between daily and sub-daily rainfall attributes over the pluviograph record is assumed to be

[1] The term 'hierarchy' is used to highlight that assumptions in each row also apply for all subsequent rows

	representation of climate variability.	stationary.
No pluviograph data, and extended daily data	High, as recorded pluviograph data is unavailable.	Partial regionalisation. Nearby pluviograph records assumed to be representative of at-site daily/sub-daily attributes.
No pluviograph data nor daily data available	High, as recorded pluviograph data is unavailable.	Complete regionalisation. Model parameters and/or daily/sub-daily fragments derived using nearby daily and pluviograph records.

3.2. Description of continuous rainfall modelling approaches

In this report, four conceptual approaches to continuous rainfall simulation are described which are designed to simulate the behaviour of historical rainfall variability at sub-daily and longer timescales. These methods include:

- Event-based models, such as the Disaggregated Rectangular Intensity Pulse (DRIP) model;
- Poisson cluster models, including the Bartlett-Lewis Rectangular Pulse and Neyman-Scott Rectangular Pulse family of models;
- Multi-scaling models, such as the canonical and microcanonical cascades family of models; and
- Nonparametric resampling models, such as the *k*-nearest neighbour method of fragments approach.

Each of these models has been developed specifically to represent sub-daily rainfall, and most have been the subject of several decades of extensive research and refinement. Attributes associated with these models are summarised in **Table 4**, and each of these models are described in more detail in the following sections.

3.2.1. Event-based models

Also known as 'alternating renewal' or 'profile-based' models, event-based models break the rainfall process into a series of events characterised by inter-arrival time, storm duration and mean storm intensity. Early work on such models by Eagleson (1978) involved simulating rainfall using a Poisson arrival process, the time between events and the event duration distributed exponentially, and the storm event depth following a gamma distribution. Since this time these models have undergone significant development, including the elucidation of the self-similarity concept, in which storms are found to exhibit similar internal structure despite differing durations and storm depths, thus providing a basis for the disaggregation of storm events into within-storm temporal patterns (e.g. Woolhiser and Osborne, 1985; Koutsoyiannis and Foufoula-Georgiou, 1993), and the development of a generalised exponential distribution for representing inter-storm and storm durations (Lambert and Kuczera, 1998).

The Disaggregated Rectangular Intensity Pulse (DRIP) model was developed by Heneker *et al* (2001) with the view to addressing several perceived deficiencies in existing event-based models, particularly with regard to the simulation of extreme rainfall and aggregation statistics. The DRIP modelling process is divided into two distinct stages. The generation stage (**Figure 14a**) is represented by three random variables: dry spell or inter-event time t_a, the wet spell or storm duration t_d, and the average intensity, i, with t_a and t_d both described by a generalised exponential distribution and the intensity described by a generalised Pareto distribution. In the second stage, the individual events are disaggregated through a constrained random walk (**Figure 14b**) to represent the rainfall temporal pattern for each event.

Table 4: Major classes of continuous simulation models, and associated attributes

Conceptual approach	Specific implementations and key references	Regionalised methods available / under development?	Software currently available for use by practitioners	Able to handle missing data	Capable of simulating the seasonal cycle?	Capable of simulating the diurnal cycle?	Capable of simulating multi-scale persistence	Developed methodology available for incorporation of climate change
Event based models	DRIP (Heneker *et al*, 2001)	Jennings *et al* (2009)	Y	Y	Y	N	Within-spell simulated; between-spell or low-frequency not simulated.	N
Poisson cluster models	Bartlett-Lewis and Neyman-Scott Rectangular Pulse models Eagleson (1978); Rodriguez-Iturbe *et al* (1984; 1987a,b; 1988)	Gyasi-Agyei (1999); Gyasi-Agyei and Parvez Bin Mahbub (2007); Cowpertwait and O'Connell (1997)	N	Y	Y	N	Within-spell simulated; between-spell or low-frequency not simulated.	N
Nonparametric re-sampling	*k*-nearest-neighbour method of fragments (Sharma and Srikanthan, 2006)	Westra and Sharma (2009)	N	Y	Y	Y	Within-spell simulated; within-day simulated; low-frequency conditional on daily model	N
Multi-scaling models	Canonical and microcanonical cascades Schertzer and Lovejoy (1987) Gupta and Waymire (1993)		N	Y	Y	N	Within spell partially simulated; low-frequency conditional on daily model	N

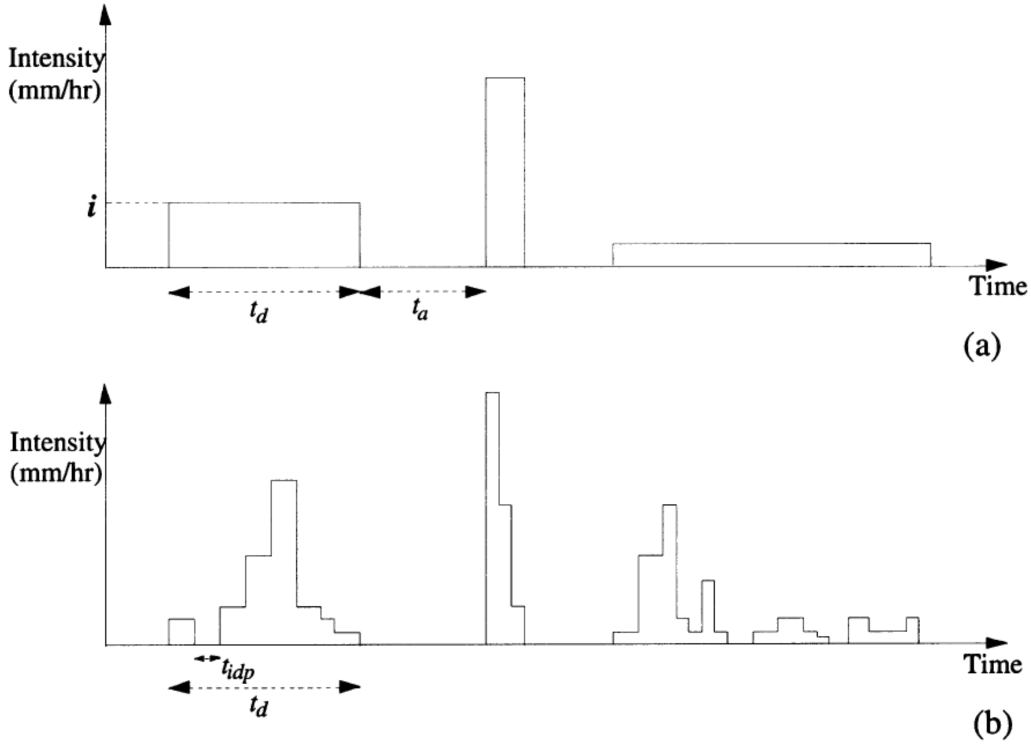

Figure 14: The Disaggregated Rectangular Intensity Pulse model (extracted from Heneker *et al*, 2001).

Recently, DRIP has been extended to any location where sufficient daily data is available, thus greatly augmenting the domain of the approach. The basis of this regionalisation is a 'master-target' scaling relationship in which model calibration is undertaken at a 'master' site with a long pluviograph record which is then updated and scaled to the 'target' site of interest using the information from either a short pluviograph or daily rainfall record (Jennings *et al*, 2009), with testing providing encouraging results for separations of up to 190 km between the master and the target.

3.2.2. Poisson cluster models

A related class of models are the Poisson cluster models, which are a generalisation of the event models proposed by Eagleson (1978) and were developed due to the observation that rainfall occurs as clusters of storm cells (Kavvas and Delleur, 1981). In the most general form, the Poisson cluster models simulate rainfall using clusters of rainfall cells temporally displaced from a storm centre, with the Neyman-Scott and Bartlett-Lewis rectangular pulse models developed by Rodriguez-Iturbe *et al* (1984; 1987a,b; 1988) in the context of rainfall simulation being two popular alternatives.

The Bartlett-Lewis and Neyman-Scott point process models are shown in **Figure 15a**, with both models assuming a Poisson arrival process (rate λ). The basic form of the Bartlett-Lewis model then simulates the arrival of cells as another Poisson process (rate β), with the duration of activity of each storm being described by an exponential distribution (parameter γ) and the cell depth and duration also distributed using an exponential distribution (parameters $1/\mu_x$ and η). In contrast, the Neyman-Scott model assumes a random number of cell arrivals independent and identically distributed around the storm centre, with the number of cell arrivals following a geometric or Poisson distribution (mean μ_c) and the random depth and duration both following an exponential distribution (parameters $1/\mu_x$ and η). The rectangular pulse part of both models is shown in **Figure 15b**, in which the evolution of the storm is simply described as the addition of each of the simulated storm cells.

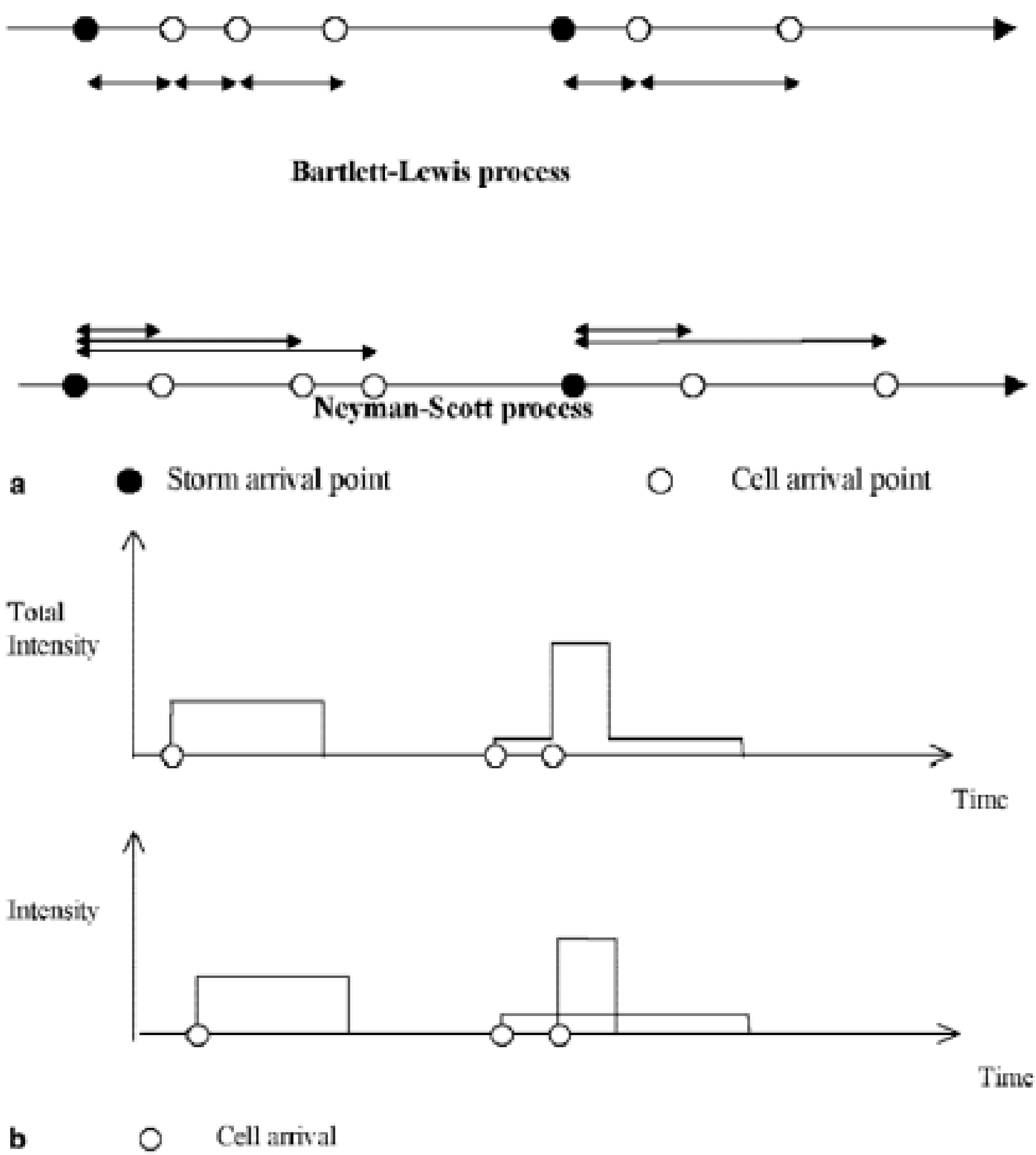

Figure 15: (a) Schematic for Poisson cluster point-process models; (b) schematic for the rectangular pulse model (extracted from Onof *et al*, 2000).

Since these early papers, a number of developments have been made to both modelling approaches. For example the Bartlett-Lewis approach has been adapted for disaggregation from daily to hourly data through a conditional simulation approach (Glasbey *et al,* 1995) or a proportional adjustment approach (Koutsoyannis and Onof, 2001). Additional developments to the Bartlett-Lewis model include the introduction of a high-frequency jitter to produce more irregular and realistic rainfall sequences (Onof and Wheater, 1994; Gyasi-Agyei and Willgoose, 1997), the development of an approach to estimate model parameters using only daily data for cases where sub-daily data are unavailable or insufficiently reliable (Smithers *et al*, 2002), and the development of approaches for parameter regionalisation by Gyasi-Agyei (1999) and Gyasi-Agyei and Parvez Bin Mahbub (2007). The Neyman-Scott model also has undergone significant development, such as parameter regionalisation by regressing model parameters on site variables such as altitude (Cowpertwait and O'Connell, 1997), spatial generalisation by the introduction of an additional parameter to represent cell radius (Cowpertwait *et al*, 2002), and the development of a mixed model to allow the supposition of independent rainfall processes such as convective and stratiform rainfall (Cowpertwait, 2003).

Empirical and analytical comparisons of the two models are provided by Velghe *et al* (1994) and Cowpertwait (1998), respectively, with a detailed review of Poisson-cluster models provided in Onof *et al* (2000).

3.2.3. Multi-scaling models

Multi-scaling models are a class of disaggregation models that take advantage of the observation that rainfall behaves as a "scale-invariant" process (e.g. Mandelbrot, 1982; Lovejoy and Maldelbrot, 1985, Schertzer and Lovejoy, 1987; Lovejoy and Schertzer, 1990; Gupta and Waymire, 1993; Onof *et al*, 2000), such that once fluctuations at a given scale are understood, those at other scales can be deduced and need not be specified independently. This allows for the generation of synthetic high-resolution rainfall sequences based on observed or generated rainfall at coarser resolutions, with various multi-scaling approaches applied in hydrology to disaggregate from daily to fine-scale sub-daily rainfall (Olsson and Berndtsson, 1998; Menabde *et al*, 1999; Menabde and Sivapalan, 2000; Sivakumar, 2001).

Two popular models are the canonical and microcanonical versions of the discrete multiplicative random cascade (Schertzer and Lovejoy, 1987; Gupta and Waymire, 1993; Over and Gupta, 1994, 1996), and these are described in detail in Molnar and Burlando (2005). The structure of these models is shown in **Figure 16** using a branching number b = 2. Here, the ith interval after n levels of subdivision is denoted Δ^i_n, with dimensionless spatial scale defined as $\lambda_n = b^{-n}$.

The distribution of mass then occurs via a multiplicative process through all levels n of the cascade, so that the mass μ_n in subdivision Δ^i_n is:

$$\mu_n(\Delta_n^i) = r_0 \lambda_n \prod_{j=1}^{n} W_j(i)$$

where r_0 is an initial depth at n = 0 and W is the cascade generator. The difference between the canonical and microcanonical models is the treatment of W, with mass preserved on average for the canonical model and exactly between the n levels in the cascade for the microcanonical model.

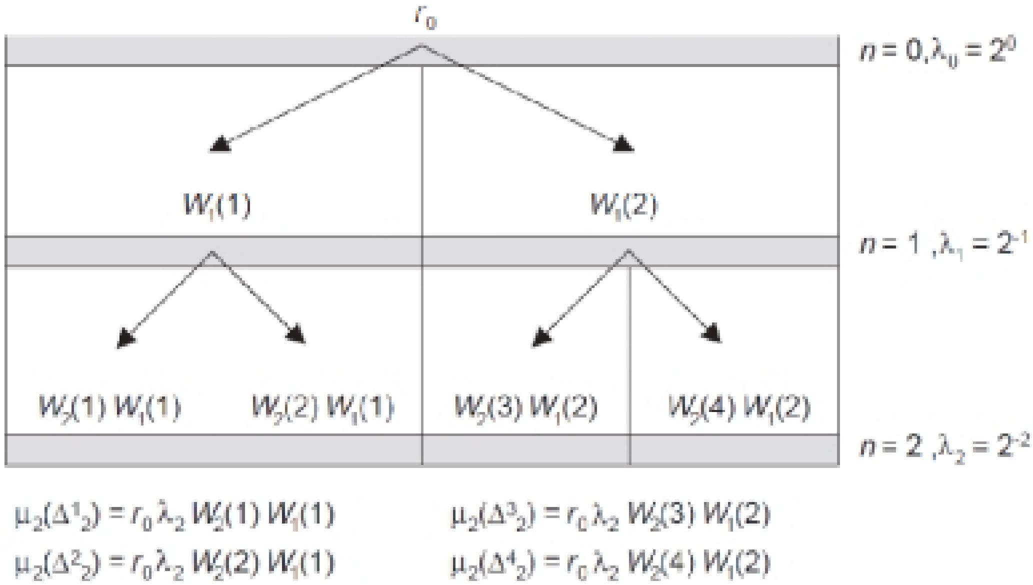

Figure 16: Framework of canonical random cascade model with branching number *b* = 2 and cascade generator W for scales n = 0, 1 and 2. r_0 denotes rainfall amount at scale 0, which in many applications corresponds to daily rainfall (extracted from Molnar and Burlando, 2005).

Two recent comparisons have been conducted of the canonical and microcanonical models. The first, by Molnar and Burlando (2005) using 20 year 10-minute rainfall records from the MeteoSwiss station in Zurich (1979-1998), found that canonical cascades are generally better at reproducing the distribution of rainfall at the 10-minute scale, whereas both models simulated the growth of intermittency across scales well. Although both models reproduced annual maxima properly, performance deteriorated for longer durations, suggesting potentially significant problems in simulating rainfall extremes. Finally, rainfall variability was found to be best simulated through the canonical models. Pui *et al* (2009) also compared both using Sydney Observatory Hill 6-minute incremented continuous rainfall data from 1916 to 2001, and found that the microcanonical model overestimated hourly variance by a large margin, whereas the canonical cascades model slightly underestimated variance. Both models were found to significantly underestimate wet spell length, with the canonical model in particular found to be poor in simulating fine-scale persistence structures.

Finally, a number of researchers have shown that the inherent structures in rainfall are much more complex than what can be represented by low-dimensional chaotic or simple multi-fractal multiplicative random cascade models (Koutsoyiannis and Pachakis, 1996; Gaume *et al*, 2006), such that fitting the scaling model alone will not guarantee all the relevant attributes of the data will be adequately reproduced (Sivakumar and Sharma, 2008).

3.2.4. Nonparametric re-sampling models

Non-parametric re-sampling models are models which conditionally resample from the historical dataset. An attraction of this framework is that by sampling directly from the data they do not require the specification of distribution functions for the occurrence and amounts processes in precipitation (e.g. Wilks and Wilby, 1999). Examples include the use of a simulated annealing algorithm for generating precipitation sequences (Bardossy, 1998) and the application of a *k*-nearest neighbour (*k*-NN) bootstrapping approach by Lall and Sharma (1996) which has been further developed by Rajagopalan and Lall (1999), Buishand and Brandsma (2001) and Yates et al (2003), and Apipattanavis et al (2007).

At the sub-daily timescale, a *k*-nearest neighbour method of fragments (MOF) approach has been developed by Sharma and Srikanthan (2006), in which temporal dependence is maintained at the daily timescale, and followed by the resampling of fragments at the sub-daily scale conditional to daily rainfall amount and the wetness state of the previous and next days.

The method takes as its starting point the availability of extended daily data, which may be derived directly from the instrumental record or through the stochastic generation of daily rainfall sequences such as via the model described in Mehrotra and Sharma (2007). The algorithm for generating continuous rainfall sequences is therefore as follows:

1. From daily rainfall ($R_i = \sum_m X_{i,m}$) where *m* represents the number of sub-daily increments, obtain the sub-daily fragment ($f_{i,m} = X_{i,m}/R_i$) such that the sum of all sub-daily fragments for each day is unity.
2. To disaggregate daily rainfall R_t at time *t*, form a moving window of length *l* days centred around day *t.* Define *l* as 15 days if the historical record is longer than 40 year and 30 days if shorter than 20 years. Interpolate for intermediate record lengths. Segregate historical rainfall data into the following four rainfall classes:

   CLASS 1: $R_j \geq 0|(R_{j-1} = 0, R_{j+1} = 0)$
   CLASS 2: $R_j \geq 0|(R_{j-1} \geq 0, R_{j+1} = 0)$
   CLASS 3: $R_j \geq 0|(R_{j-1} = 0, R_{j+1} \geq 0)$
   CLASS 4: $R_j \geq 0|(R_{j-1} \geq 0, R_{j+1} \geq 0)$

   where *j* represents a day falling within the moving window centred on the current day *t.*
3. Identify the class corresponding to the daily rainfall R_t that is to be disaggregated. Denote the class c_t where $c_t \in [1-4]$.
4. Identify the *k* nearest neighbours of the conditioning vector [R_t] as the days corresponding to the *k* lowest absolute departures $|R_t - R_j|$ where $c_j \equiv c_t$. Specify $k = \sqrt{n}$ where *n* represents the sample size of the class members falling within the moving window. Sample neighbour *i* from the following conditional distribution:
   $$p(i) = \frac{1/i}{\sum_{j=1}^{k} 1/j}$$
   where *p*(*i*) represents the probability of selecting neighbour *i*, with *i* = 1 denoting the neighbour having the smallest absolute departure. Denoting (*i*) as the observation associated with the *i*th neighbour, the disaggregate series can be specified as $X_{t,m} = R_t \times f_{(i),m}$.
5. Increment *t* and repeat steps 2 to 4 until disaggregation is completed.

This approach has been tested using continuous data in Sydney Observatory Hill, and was found to perform well in reproducing a range of statistics including extreme statistics such one-hour IFD behaviour, together with persistence attributes at a range of scales (see also Mehrotra and Sharma, 2007; Pui *et al*, 2009).

The above methodology was originally developed for locations with extended continuous data. Nevertheless, a limitation of this approach is that regardless of how much data is available, it is impossible to exceed the maximum recorded rainfall event through such a re-sampling algorithm (Furrer and Katz, 2008). Furthermore, as discussed previously, pluviograph data is often unavailable at the location of interest, which can severely restrict the application of this method.

To this end, techniques for regionalisation are currently being developed, with preliminary results suggesting that sub-daily fragments from nearby pluviograph stations can be substituted for at-site pluviograph stations to form the basis for the re-sampling algorithm, potentially extending the approach to any location for which daily data is available (Westra and Sharma, 2009). Sampling from a greater number of locations also provides a greater density of observations at the tail end of the distribution, therefore partially overcoming the limitations associated with representing the extremes described by Furrer and Katz (2008). The basis for identifying nearby locations was described at length in **Section 2** of this report, with results suggesting that stations that are within a similar latitude band and distance from coast are likely to be substitutable, and with sampling recommended from multiple nearby stations to avoid any possible biases due to reliance on only a single nearby rain gauge. Furthermore, work is also underway to regionalising the daily rainfall generator of Mehrotra and Sharma (2007) by using a similar approach to draw on nearby daily rainfall gauges, thereby extending non-parametric re-sampling approach of Sharma and Srikanthan (2006) to any location in Australia.

3.3. Validation of continuous rainfall simulation models

The validation of the continuous rainfall simulation models, preferably on statistics not used in the calibration of model parameters, is an important step in the development of recommendations for more widespread use of continuous rainfall approaches as a viable alternative to Intensity-Frequency-Duration (IFD) estimates in design flood estimation. Due to the complexity of rainfall (e.g. see discussion of high-dimensional chaotic properties of rainfall in Koutsoyiannis and Pachakis, 1996; Gaume *et al*, 2006), it is likely that none of the above models will be able capture all the attributes of rainfall in all regions throughout Australia, such that in many cases the appropriate model will depend on the specific application.

Several studies are available comparing continuous simulation models using a subset of time scales. For example, Srikanthan *et al* (2005) compare two daily simulation models, namely the transition probability matrix (TPM) model of Haan *et al* (1976) and Srikanthan and McMahon (1985) with a non-parametric daily model for occurrences and amounts developed by Harrold *et al* (2003a,b), considering a combination of daily, monthly and annual statistics and finding that the nonparametric model provided marginally better performance at the cost of greater model complexity. Various other studies compared several of the previously described models using overseas data, such as the Poisson cluster models in the United Kingdom, and continental Europe (Onof *et al*, 2000), and a review of canonical and microcanonical cascade models in Zurich, Switzerland by Molnar and Burlando (2005).

Two studies have been completed recently in the context of Australian rainfall at timescales that include the sub-daily timescale. The first, by Frost *et al* (2004), compared a 30 parameter version of the DRIP model of Heneker *et al* (2001) with a six parameter version of the single-point version of the spatial Neyman-Scott Rectangular Pulse (NSRP) model developed by Cowpertwait *et al* (2002). The models were compared using continuous rainfall data from 10 major cities and regional centres: Adelaide, Alice Springs, Brisbane, Cairns, Darwin, Hobart, Melbourne, Perth, Sydney and Townsville, with all stations with the exception of Adelaide having 45 years or more data. The models were compared using a large number of statistics which considered results at the 1, 6 and 24-hour aggregation levels, together with a large range of daily, monthly and annual aggregate statistics. The outcomes of the validation are summarised briefly below:

- Wet spell and dry spell probabilities at short (1,6 and 24 hour) timescales was reproduced well by DRIP, and less well by NSRP particularly with regard to the simulation of the seasonality of dry spell durations;
- The daily mean, standard deviation and skew was reproduced well by both models, although NSRP was found to outperform DRIP in reproducing daily autocorrelation statistics;
- The NSRP model simulates the annual rainfall distribution more satisfactorily than DRIP, with DRIP underestimating annual variance; and
- The NSRP was found to simulate IFD curves well for the 1, 6 and 24 hour timescales. DRIP was able to simulate finer (0.1 hr) timescales as well, and was found to perform satisfactorily in reproducing 1, 6 and 24 hour rainfall with the exception of the underestimation of 1 hour rainfall in Sydney and Melbourne for 2-10 yr recurrence intervals, and a severe overestimation of the short-duration (0.1hr) statistics for some tropical sites.

The conclusion of this work is that, despite the differences described above, both models provide adequate reproduction over a wide range of statistics, with little overwhelming evidence in favour of either model structure. The DRIP model has since been included in the CRC for Catchment Hydrology's toolkit, as it is capable of generating sub-hourly rainfall.

A second comparison study by Pui *et al* (2009) focused on the capacity of a range of models to disaggregate from daily to sub-daily data, with the implicit assumption that daily data would be available or can be adequately generated at the location of interest. The models examined include the canonical and microcanonical cascade models using the methodology described in Gupta and Waymire (1993), Over and Gupta (1994; 1996) and Molnar and Burlando (2005), the Randomised Bartlett Lewis Model (RBLM) coupled with a proportional adjusting procedure (Koutsoyannis and Onof, 2001), and the nonparametric method of fragments (MOF) of Sharma and Srikanthan (2006), with all testing conducted using a single pluviograph record at Sydney Observatory Hill from 1916 to 2001. As this study has yet to be published, it is reproduced in **Appendix 1** of this report.

The models were evaluated based on their ability to simulate rainfall variability and intermittency, within-day wet spells, and extreme rainfall percentiles. The outcomes of the study are summarised as follows:

- All models were found to reproduce mean hourly rainfall well, although the microcanonical model overestimated hourly variance by a large margin. In contrast, the canonical model slightly underestimates hourly variance;

- Wet spells were found to be captured best by the MOF model, with the mean spell length per day and the mean number of wet spells occurrences per day performing well. The canonical model was found to fail in generating within-day wet spells longer than four hours and overestimated the occurrences of short spells (1-2 hours), suggesting that it is unable to properly simulate rainfall persistence; and
- The MOF model performs well in reproducing IFD behaviour at an hourly time scale. In contrast, the canonical cascades model underestimated the extreme rainfall statistics, the microcanonical cascades model significantly overestimated the extreme rainfall statistics, and the RBLM model was found to be poor in reproducing low recurrence interval design rainfall values;

The study concludes that the MOF model outperforms all the other models in reproducing the evaluated rainfalls statistics, with the RBLM model performing better than the cascade models although with slightly inflated simulation of proportions at an hourly timescale as well as an underestimation of extreme rainfall at low return periods.

Unfortunately the studies of Frost *et al* (2004) and Pui *et al* (2009) are not directly comparable. The emphasis of the Pui *et al* (2009) study was on disaggregation from daily to sub-daily rainfall rather than on continuous simulation, and used a version of the Poisson cluster models specifically adapted for disaggregation. Furthermore, the non-parametric method of fragments approach was developed after the study by Frost *et al* (2004) and therefore has not been comprehensively tested against alternative continuous simulation models.

Nevertheless, the results of both studies as summarised in **Table 5** show that, with the exception of the canonical and microcanonical cascades models, all remaining model structures are capable of reproducing most of the statistics analysed, with the selection of the suitable model for the application in question likely to be determined by a combination of intended application and data availability.

Table 5: Summary of validation results from various studies comparing continuous simulation approaches. References are F04 (Frost *et al*, 2004), MB05 (Molnar and Burlando, 2005) and P09 (Pui *et al*, 2009)

Conceptual approach	Reproduction of sub-daily statistics (e.g. mean, standard deviation, skew, autocorrelation, and dry- and wet-spells)	Reproduction of aggregate (daily, monthly, annual) statistics?	Reproduction of IFD statistics?	Reproduction of low-frequency (i.e. interannual, interdecadal) variability?
Event based models (DRIP)	Good, although slight overestimation of lag 1 hr and underestimation of lag 24 hr autocorrelation (F04)	Most daily statistics reproduced well with exception of daily autocorrelation. Annual distribution reasonable at most locations but with underestimation of annual variance. (F04)	Generally good with some exceptions particularly at sub-hourly scale (F04)	Untested, but likely to be poor.
Poisson cluster models (NSRP/RBLM)	Generally good, although the NSRP performed poorly for wet spell and dry spell statistics (F04)	Most daily statistics reproduced well. Annual distribution for NSRP reasonable at most locations (F04)	Good (F04). RBLM poorly simulates low ARI design rainfall values (P09)	Untested, but continuous simulation versions (e.g. NSRP) likely to be poor.
Nonparametric (Method of Fragments)	Good (P09)		Good (P09)	Disaggregation model only, so results conditional to daily simulation model
Cascades (canonical and microcanonical)	Hourly variance significantly overestimated by microcanonical model and slightly underestimated by canonical model. Cascades model also underestimates wet spell length (P09)		Questionable or poor reproduction of most IFD statistics (MB05; P09)	Disaggregation model only, so results conditional to daily simulation model

4. Conclusions and future stages

As described in the Background section, this report describes the outcome of the first of three stages of work to develop, test and validate the procedures for generating continuous rainfall sequences at point locations in Australia, as well as suggesting modifications in existing methods to account for the impact of climate change.

This report has focused on the identification and description of a range of alternative models that are capable of reproducing continuous sequences of rainfall at sub-daily and longer timescales, as well as providing a summary of a number of validation studies for each of the models. The outcomes of this review are that DRIP, the Poisson cluster class of models, and the MOF model, are each capable of simulating most of the statistics of rainfall, including IFD characteristics which are essential for simulation of flood behaviour. Nevertheless, the testing of the models in Australia has not been comprehensive, particularly with relation to the MOF model and regionalised versions of the remaining models, and recommendations for addressing these issues are described below.

The other contribution of this report was the examination of daily/sub-daily properties of rainfall, with a focus on (a) the scaling behaviour of rainfall, and (b) the timing of rainfall as described by the diurnal cycle. This research showed that there was remarkable similarity in the behaviour of sub-daily rainfall conditional to daily rainfall amount for different locations, provided that the locations were at a similar latitude in the case of daily/sub-daily scaling and amplitude of the diurnal cycle, and that the locations were at a similar distance to the coast in terms of the timing of the diurnal cycle. This is reassuring given the limited availability of sub-daily rainfall in Australia compared to daily rainfall, suggesting that properties of sub-daily rainfall using data from nearby locations can be used to develop continuous rainfall sequences at the location in question provided an appropriate technique is used for the regionalisation.

To provide validation of the continuous rainfall simulation as a total system for use in flood estimation and engineering design, there are a number of outstanding questions which require further work. These are described as follows.

4.1. Regionalisation of the method of fragments method

The development of a regionalised version of the method of fragments method developed by Sharma and Srikanthan (2006) is an important outcome of this project and work is well underway in developing a complete method. The proposed approach was described earlier, and is based on sampling sub-daily fragments from multiple ‘nearby’ continuous rainfall locations with similar daily/sub-daily rainfall properties, with the determination of ‘nearby’ locations likely to include the latitude and distance to coast.

Although the conceptual approach has been well developed, there are a number of outstanding issues which require addressing. These include identification of the number of nearby stations used for resampling, and the handling of stations with different record lengths to ensure the sampling is unbiased to a particular climate regime. Furthermore, the method has yet to be carefully tested, and this testing will no doubt lead to further refinement.

It is furthermore proposed that this work be extended to develop a fully regionalised approach, by also incorporating the capability of re-sampling daily rainfall characteristics from nearby daily rainfall sampling locations. This will ensure that both daily and sub-daily rainfall can be generated at any gauged or ungauged location in Australia.

Based on the positive results derived from preliminary testing, it is recommended that the regionalised method of fragments methodology be finalised in the next project stage.

4.2. Validation of continuous simulation models

As described in **Section 3** of this report, significant validation already has been conducted on all the models described, and therefore a complete review of each of the models is unwarranted. Nevertheless, the following gaps were identified which require further investigation:

- The MOF model should be compared to the DRIP and/or the NSRP model for multiple locations around Australia, such as the locations used by Frost *et al* (2004) in validating the DRIP and NSRP models; and
- Due to the importance of simulating antecedent conditions prior to the flood-producing rainfall event as a justification for continuous simulation in flood estimation, the joint probability of antecedent moisture statistics (e.g. 1, 7, 30 and 90 day aggregate rainfall prior to extreme rainfall events) and design rainfall events should be assessed as part of the validation exercise.

Furthermore, as described previously, the validation studies completed to-date have focused on results derived from models calibrated using extended at-site pluviograph data. In contrast, the value of continuous simulation is likely to be greatest at locations where long instrumental records are unavailable, such that the more important question is how the methods work in regionalisation.

With the exception of the multi-scaling models, all the major model classes have regionalised versions available or under development. As such, it is recommended that the regionalisation capabilities of DRIP (e.g. Jennings *et al*, 2009), regionalised versions of the Poisson cluster model (e.g. Gyasi-Agyei, 1999; Gyasi-Agyei and Parvez Bin Mahbub, 2007; Cowpertwait and O'Connell, 1997) and the nonparametric resampling model (e.g. Westra *et al*, 2009) be tested for a range of locations around Australia. The validation statistics should include those developed by Frost *et al* (2004), together with testing of the preservation of antecedent moisture characteristics prior to extreme rainfall events of various storm durations.

Finally, as continuous rainfall simulation results are expected to be used in rainfall-runoff models to generate flow series, the testing of differences in runoff assuming varying catchment characteristics for each of the continuous simulation approaches is warranted.

4.3. Incorporation of climate change

To accurately incorporate climate change projections into continuous rainfall sequences, it is necessary to capture projected changes in:

- Seasonal and annual aggregate rainfall statistics, including mean, variance and skew;

- Large-scale global or regional climate drivers such as ENSO which drive low-frequency rainfall variability;
- The behaviour of rainfall extremes, such as the 1 in 100 year rainfall event with durations from fine-scale sub-daily (e.g. 10 minute) through to multiple consecutive days;
- The relative distributions of dry and wet spells associated with the differing projections for rainfall averages and extremes; and
- The character of sub-daily rainfall attributes such as the wet fraction for each daily rainfall occurrence, and the diurnal cycle.

There is no methodology available that is able to capture the full range of changes which are likely to occur as a result of anthropogenic climate change, with climate impacts assessments usually considering only those aspects of future change which are most relevant for the intended study. For example, in considering likely changes in flood risk, the emphasis has been on applying regional climate models to derive change factors for short-duration events of a suitably rare recurrence interval (e.g. Abbs, 2007; Abbs and Rafter, 2008). In contrast, water resource assessments often focus on seasonal changes in rainfall such as described in CSIRO (2007), with less emphasis on changes to fine-temporal or special-scale rainfall patterns.

It is generally understood that extreme rainfall is likely to increase over much of Australia, regardless of the direction of change of seasonal or annual rainfall, due to the strong physical link between temperature increases and the water holding capacity in the atmosphere (refer to Westra *et al*, 2009 and references therein, attached as **Appendix 2** of this report). This suggests that the relationship between antecedent conditions and flood-producing rainfall is likely to change, with more extreme rainfall likely to fall on drier catchments.

There are at least two general classes of approaches to generating continuous sequences of rainfall under a changed climate. The first, known as daily scaling (e.g. Chiew, 2006), involves the examination of the relative change in rainfall amounts using daily rainfall outputs from one or more General Circulation Models (GCMs) under historical and future conditions, with different scaling factors applied across the range of rainfall percentiles ensuring that different factors can be applied to the averages and extremes of rainfall. A limitation of this approach is the direct reliance on GCM outputs of rainfall, which is generally considered to be amongst the least reliable of the GCM variables (e.g. Johnson and Sharma, 2009).

The second approach, known as statistical (or empirical) downscaling, arguably represents the most promising tool to generate extended continuous rainfall sequences (e.g. Fowler *et al*, 2007; Wilby *et al*, 2009). The benefits of this approach is that it is based on maintaining the conditional relationship between historical rainfall and a suite of large-scale climate variables for which GCMs have a demonstrated capability of simulating well, and is therefore likely to be the most robust approach for simulating the full range of changes likely to occur. For example, a recently developed suite of parametric and non-parametric approaches to generate daily rainfall has proved successful in simulating a range of statistics of historical climate (Mehrotra et al, 2004; Mehrotra and Sharma, 2005, 2006, 2007a,b), although the method still requires refinements to correctly simulate low-frequency variability at inter-annual timescales, and also requires testing in terms of its ability to reproduce daily rainfall extremes (pers. coms. Raj Mehrotra). Finally, to our knowledge no statistical downscaling methodology is available that also allows reproduction of sub-daily rainfall sequences. This constitutes an important area of future research.

Unlike the continuous simulation of rainfall to reproduce historical rainfall statistics, continuous simulation for a future climate is still at an early stage of research, with no tested methodology currently available capable of reproducing continuous sequences suitable for flood estimation. Two options for continuous simulation for a future climate that are viable are: (a) the development of a two-staged stochastic downscaling alternative, that first downscales (in space) GCM simulations to daily point rainfall, and then downscales (in time) the daily point rainfall to a sub-daily scale using a disaggregation (with possible conditioning on exogenous variables) alternative, and (b) a dynamical downscaling option that can be used to formulate a scaling transformation model that enables modification of observed continuous records to correspond to likely future conditions. It is recommended that work be commissioned to support research endeavours to this end.

5. References

Abbs, D., 2007, The impact of climate change on extreme rainfall and coastal sea levels over south-east Queensland - Part 2: A high-resolution modelling study of the effect of climate change on the intensity of extreme rainfall events, consultancy report prepared for the Gold Coast City Council, CSIRO, 39pp.

Abbs, D. & Rafter, T., 2008, The effect of climate change on extreme rainfall events in the Western Port Region, CSIRO Marine and Atmospheric Research (available at http://www.wpga.org.au/ppp.asp).

Apipattanavis, S., Podesta, G., Rajagopalan, B. & Katz, R.W., 2007, A semiparametric multivariate and multisite weather generator, *Water Resources Research,* Vol. 43, W11401, doi: 10.1029/2006WR005714.

Bardossy, A., 1998, Generating precipitation time series using simulated annealing, *Water Resources Research*, Vol. 34, No. 7, pp 1737-1744.

Beecham, S. & Chowdhury, R.K., 2009, Temporal characteristics and variability of point rainfall: a statistical and wavelet analysis, *International Journal of Climatology,* DOI: 10.1002/joc1901.

Buishand, T.A., & Brandsma, T., 2001, Multisite simulation of daily precipitation and temperature in the Rhine basin by nearest-neighbour resampling, *Water Resources Research*, 37(11), 2761-2776.

Chiew, F.H.S., 2006, An overview of methods for estimating climate change impact on runoff, *30th Hydrology and Water Resources Symposium, 4-7 December 2006,* Launceston, Tasmania.

Cowpertwait, P.S.P. & O'Connell, P.E., 1997, A regionalised Neyman-Scott model of rainfall with convective and stratiform cells, *Hydrology and Earth System Sciences,* 1, 71-80.

Cowpertwait, P.S.P., 1998, A Poisson-cluster model of rainfall: High-order moments and extreme values, *Proc. R. Soc. Lon. Ser. A.,* 454, 885-898.

Cowpertwait, P.S.P., Kilsby, C.G. & O'Connell, P.E., 2002, A space-time Neyman-Scott model of rainfall: Empirical anlsysis of extremes, *Water Resources Research*, 38(8):6.

Cowpertwait, P.S.P., 2003, Mixed rectangular pulses models of rainfall, *Res. Lett. Inf. Math. Sci.,* 5:61-70.

CSIRO, 2007, Climate Change in Australia, Technical Report 2007 (available from www.climatechangeinaustralia.com.au)

Dai, A., 1999, Recent changes in the diurnal cycle of precipitation over the United States, *Geophysical Research Letters*, Vol. 26, No. 3., 341-344.

Dai, A., Giorgi, F. & Trenberth, K.E., 1999, Observed and model-simulated diurnal cycles of precipitation over the contiguous United States, *Journal of Geophysical Research*, Vol. 104, No. D6, 6377-6402.

Dai, A., 2001, Global Precipitation and Thunderstorm Frequencies - Part II: Diurnal Variations, *Journal of Climate*, Vol. 14, 1112-1128.

Dai, A., 2006, Precipitation characteristics in eighteen coupled climate models, *Journal of Climate*, Vol. 16, 4506-4630.

Eagleson, P.S., 1978, Climate, Soil and Vegetation 2. The distribution of annual precipitation derived from observed storm sequences. *Water Resources Research*, 14(5): 713-721.

Fowler, H.J., Blenkinsop, S. & Tebaldi, C., 2007, Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling, *International Journal of Climatology*, doi: 10.1002/joc.1556.

Frost, A., Srikanthan, R. & Cowpertwait, P., 2004, Stochastic generation of rainfall data at subdaily timescales: a comparison of DRIP and NSRP, *Cooperative Research Centre for Catchment Hydrology Technical Report, Report number 04/9.*

Furrer, E.M. & Katz, R.W., 2008, Improving the simulation of extreme precipitation events by stochastic weather generators, *Water Resources Research*, Vol. 44, W12439, doi: 10.1029/2008WR007316.

Gaume, E., Sivakumar, B., Kolasinski, M. & Hazoume, L., 2006, Identification of chaos in rainfall temporal disaggregation: application of the correlation dimension method to 5-minute point rainfall series measured with a tipping bucket and an optical raingauge, *Journal of Hydrology*, doi: 10.1016/j.jhydrol.2005.11.034.

Glasbey, C.A., Cooper, G. & McGechan, M.B., 1995, Disaggregation of daily rainfall by conditional simulation from a point-process model, *Journal of Hydrology,* 165, 1-9.

Gupta, V.K. & Waymire, E.C., 1993, A statistical analysis of mesoscale rainfall as a random cascade, *Journal of Applied Meteorology,* 32: 251-267.

Gyasi-Agyei, Y. & Willgoose, G.R., 1997, A hybrid model for point rainfall modelling, *Water Resources Research*, 33 (7), 1699-1706.

Gyasi-Agyei, Y., 1999, Identification of regional parameters of a stochastic model for rainfall disaggregation, *Journal of Hydrology*, 223 (3-4), 148-163.

Gyasi-Agyei, Y. & Parvez Bin Mahbub, S.M., 2007, A stochastic model for daily rainfall disaggregation into fine time scale for a large region, *Journal of Hydrology*, 347, 358-370.

Haan, C.T., Allen, D.M. & Street, J.D., 1976, A Markov chain model of daily rainfall, *Water*

Resources Research, 12(3): 443-449.

Heneker, T.M., Lambert, M.F. & Kuczera, G., 2001, A point rainfall model for risk-based design, *Journal of Hydrology*, 251: 65-87.

Higgins, R.W., Jano-wiak, J.E. & Yao, Y.P., 1996, A gridded hourly precipitation database for the United States (1963-1993), in *NCEP/Climate Prediction Centre ATLAS No. 1*, 47pp., U.S. Dep. Of Comm., Washington, D.C.

Harrold, T.I., Sharma, A. & Sheather, S.J., 2003a, A nonparametric model for stochastic generation of daily rainfall occurrence, *Water Resources Research*, 39(10): 1300, doi: 10.1029/2003WR002182.

Harrold, T.I., Sharma, A. & Sheather, S.J., 2003b, A nonparametric model for stochastic generation of daily rainfall amounts, *Water Resources Research*, 39(12): 1343, doi: 10.1029/2003WR002570.

Jennings, S.A., Lambert, M.F., Kuczera G. (2009), A High Resolution Point Rainfall Model Calibrated to Short Pluviograph or Daily Rainfall Data, *Journal of Hydrology*, submitted manuscipt

Johnson, F. & Sharma, A., 2009, Measurement of GCM skill in predicting variables relevant for hydroclimatological assessments, *Journal of Climate*, in press, doi: 10.1175/2009JCLI2681.1

Kavvas, M.L. & Delleur, J.W., 1981, A stochastic model of daily rainfall sequences, *Water Resources Research*, 17(4), 1151-1160.

Kikuchi, K. & Wang, B., 2008, Diurnal precipitation regimes in the global tropics, *Journal of Climate,* Vol. 21, 2680-2696, doi: 10.1175/2007JCLI2051.1.

Koutsoyiannis, D. & Foufoula-Georgiou, E., 1993, A stochastic disaggregation method for design storm and flood synthesis, *Journal of Hydrology*, 156, 193-225

Koutsoyiannis, D. & Pachakis, D., 1996, Deterministic chaos versus stochasticity in analysis and modelling of point rainfall series, *Journal of Geophysical Research*, 101 D21, 26441-26451.

Koutsoyiannis, D. & Onof, C., 2001, Rainfall disaggregation using adjusting procedures on a Poisson cluster model, *Journal of Hydrology,* 246, 109-122.

Kuczera, G., Lambert, M., Heneker, T.M., Jennings, S., Frost, A.J. & Coombes, P.J., 2006, Joint probability and design storms at the crossroads, *28th International Hydrology and Water Resources Symposium – Wollongong,* The Institution of Engineers, Australia.

Lall, U. & Sharma, S., 1996, A nearest neighbour bootstrap for time series resampling, *Water Resources Research*, 32(3), 679-693.

Lambert, M. & Kuczera, G., 1998, Seasonal generalised exponential probability models with application to interstorm and storm durations, *Water Resources Research*, 34(1), 143-148.

Leonard, M., 2009, Patterns of rainfall in space and time for use in flood risk estimation, Discussion paper prepared for the Australian Rainfall and Runoff Technical Committee and invited guests discussion forum in Melbourne on July 9th, 2009.

Lovejoy, S. & Mandelbrot, 1985, Fractal properties of rain and a fractal model, *Tellus*, 37A, 209-232.

Lovejoy, S. & Schertzer, D., 1990, Multifractals, universality classes, and satellite and radar measurements of cloud and rain fields, *Journal of Geophysical Research*, 95: 2021-2031.

Mandelbrot, B. B., The Fractal Geometry of Nature, W. H. Freeman, New York, 1982.

Mehrotra, R., A. Sharma and I. Cordery, 2004, Comparison of two approaches for downscaling synoptic atmospheric patterns to multisite precipitation occurrence, *Journal of Geophysical Research*., 109, D14107, doi:10.1029/2004JD004823.

Mehrotra, R. & Sharma, A., 2005, A nonparametric nonhomogeneous hidden Markov model for downscaling of multi-site daily rainfall occurrences, *Journal of Geophysical Research.*, 110, D16108, doi:10.1029/2004JD005677.

Mehrotra, R. & Sharma, A., 2006, A nonparametric stochastic downscaling framework for daily rainfall at multiple locations, *Journal of Geophysical Research.*, 111, D15101, doi:10.1029/2005JD006637

Mehrotra, R. & Sharma, A., 2007, Preserving low-frequency variability in generated daily rainfall sequences, *Journal of Hydrology*, doi:10.1016/j.jhydrol.2007.08.003

Mehrotra, R., & Sharma, A., 2007, A multisite stochastic downscaling model of daily rainfall occurrences with long term persistence, *MODSIM 2007 Congress 10-13 December, 2007*, Christchurch, New Zealand

Menabde, M., Seed, A. & Pegram, G., 1999, A simple scaling model for extreme rainfall, *Water Resources Research*, 35(1): 335-340, doi: 10.1029/1998WR900012.

Menabde, M. & Sivapalan, M., 2000, Modeling of rainfall time series and extremes using bounded random cascades and Levy-stable distributions, *Water Resources Research*, 36(11): 3293-3300.

Molnar, P. & Burlando, P., 2005, Preservation of rainfall properties in stochastic disaggregation by a simple random cascade model, *Atmospheric Research,* 77: 137-151.

Olsson, J. & Berndtsson, R., 1998, Temporal rainfall disaggregation based on scaling properties, Water Science and Technology, 37 (11): 73-79.

Onof, C. & Wheater, H.S., 1994, Improvements to the modelling of British rainfall using a modified random parameter Bartlett-Lewis rectangular pulse model, *Journal of Hydrology,* 157, 177-195.

Onof, C., Chandler, R.E., Kakou, A., Northrop, P., Wheater, H.S. & Isham, V., 2000, Rainfall modelling using Poisson-cluster processes: a review of developments*, Stochastic Environmental Research and Risk Assessment* 14, 384-411.

Over, T.M. & Gupta, V.K., 1994, Statistical analysis of mesoscale rainfall: dependence of a random cascade generator on large scale forcing, *Journal of Applied Meteorology*, 33, 1526-1542.

Over, T.M. & Gupta, V.K., 1996, A space-time theory of mesoscale rainfall using random cascades, *Journal of Geophysical Research*, 101 (D21), 26319-26331.

Peppler, R.A. & Lamb, P.J., 1989, Tropospheric static stability and central North American growing season rainfall, *Monthly Weather Review,* 112, 638-651.

Pui, A., Sharma, A. & Mehrotra, R., 2009, A comparison of alternatives for daily to sub-daily rainfall disaggregation, submitted to Journal of Hydrology – See Appendix 1.

Rajagopalan, B. & Lall, U., 1999, A *k*-nearest neighbour simulator for daily precipitation and other variables, *Water Resources Research*, 35(10), 3089-3101.

Rodriguez-Iturbe, I., Gupta, V.K. & Waymire, E., 1984, Scale considerations in the modelling of temporal rainfall, *Water Resources Research*, 20(11), 1611-1619.

Rodriguez-Iturbe, I., Cox, D.R. & Isham, V., 1987a, Some models for rainfall based on stochastic point processes, *Proceedings of the Royal Society London*, A410: 269-288.

Rodriguez-Iturbe, I., Febres de Power, B. & Valdes, J.B., 1987b, Rectangular pulses point processe models for rainfall: analysis of empirical data, *Journal of Geophysical Research*, 92(D8): 9645-9656.

Rodriguez-Iturbe, I., Cox, D.R. & Isham, V., 1988, A point process for rainfall: further developments, *Proceedings of the Royal Society London*, A417: 283-298.

Schertzer, D. & Lovejoy, S., 1987, Physical modelling and analysis of rain and clouds by anisotropic scaling multiplicative processes, *Journal of Geophysical Research*, 92, 9693-9714.

Scott, D., 1992, *Multivariate Density Estimation – Theory, Practice and Visualisation,* John Wiley and Sons, Inc. New York, 317pp.

Sharma, A. & Srikanthan, R., 2006, Continuous rainfall simulation: a nonparametric alternative, *30th Hydrology and Water Resources Symposium,* 4-7 December 2006, Launceston, Tasmania.

Sivakumar, B., 2001, Is a chaotic multi-fractal approach for rainfall possible? *Hydrological Processes*, 227(1-4): 1-20.

Sivakumar, B. & Sharma, A., 2008, A cascade approach to continuous rainfall data generation at point locations, *Stochastic Environmental Research and Risk Assessment*, 22: 451-459, doi: 10.1007/s00477-007-0145-y.

Smithers, J.C., Pegram, G.G.S. & Schulze, R.E., 2002, Design rainfall estimation in South Africa using Barlett-Lewis rectangular pulse rainfall models, *Journal of Hydrology*, 258, 1-4, pp. 83-99.

Srikanthan, R. & McMahon, T.A., 1985, Stochastic generation of rainfall and evaporation data, Technical Paper No. 84, Australia Water Resources Council, Canberra.

Srikanthan, R., Harrold, T.I., Sharma, A. & McMahon, T.A., 2005, Comparison of two approaches for generation of daily rainfall data, *Stochastic Environmental Research and Risk Assessment,* 19: 215-226, doi: 10.1007/s00477-004-0226-0.

Velghe, T., Troch, P.A., De Troch, F.P. & Van de Velde, J., 1994, Evaluations of cluster-based rectangular pulses point process models for rainfall, *Water Resources Research,* 30, 2847-2857.

Westra, S. & Sharma, A., 2009, Continuous rainfall simulation: estimation at ungauged locations, *32nd Hydrology and Water Resources Symposium*, Newcastle, Australia (submitted manuscript. This paper has been mostly reproduced as Section 2 of this report).

Westra, S., Varley, I., Jordan, P., Nathan, R., Ladson, A., Sharma, A. & Hill, P., 2009, Addressing climatic non-stationarity in the assessment of flood risk (in preparation – to be submitted to the Journal of Australian Water Resources – see Appendix 2).

Wilby, R.L., Troni, J., Biot, Y., Tedd, L., Hewitson, B.C., Smith, D.M. & Sutton, R.T., 2009, A review of climate risk information for adaptation and development planning, *International Journal of Climatology,* doi: 10.1002/joc. 1839.

Wilks, D.S. & Wilby, R.L., 1999, The weather generation game: A review of stochastic weather models, *Prog. Phys. Geogr.,* 23(3), 329-357.

Woolhiser, D.A. & Osborne, H.B., 1985, A stochastic model of dimensionless thunderstorm rainfall, *Water Resources Research*, 21(4), 511-522.

Yates, D., Gangopadhyay, S., Rajagopalan, B. & Strzepek, K., 2003, A technique for generating regional climate scenarios using a nearest-neighbour algorithm, *Water Resources Research*, 39(7), 1199, doi: 10.1029/2002WR001769.

Appendix 1: "A Comparison of Alternatives for Daily to Sub-Daily Rainfall Disaggregation"

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Abstract

Urban hydrology traditionally requires Intensity –Frequency – Duration (IFD) relationships to ascertain design storms for the purpose of design flood analysis. Design storm based alternatives pose uncertainty in the estimated flood as the influence of catchment antecedent conditions cannot be properly accounted for. Hence, generating continuous series of flows using stochastically generated rainfall that can better reflect antecedent characteristics presents an attractive alternative. This paper evaluates three methods of disaggregating daily rainfall to near-continuous sequences, namely, the Random Multiplicative Cascades (Microcanonical and Canonical versions), Randomized Bartlett Lewis Model (RBLM) coupled with Proportional Adjusting Procedure, and the Method of Fragments (MOF). These methods are used to perform disaggregation from daily to hourly rainfall using 86 years (1916 – 2001) of continuous observed hourly rainfall data from Observatory Hill station in Sydney, Australia. Evaluation of the methods is based on the capability of the resulting sequences to represent rainfall variability and intermittency, within-day wet spells, and extreme rainfall percentiles. While all models are found to simulate well the commonly used statistical measures such as mean and dry proportions at an hourly time step, the Microcanonical model significantly overestimates the rainfall variance. With respect to extreme value characteristics, the MOF is found to match well the observed IF relationship at an hourly scale, with the cascade models underestimating (Canonical) and overestimating (Microcanonical) extreme rainfall. The RBLM poorly simulates the low average recurrence interval (ARI) design rainfall values. An analysis of the within-day wet spell distribution shows that the cascades models underestimate mean spell lengths. The MOF model replicates the observed wet spell distribution while the RBLM also performs fairly well.

1. Introduction

A wide range of applications involving the planning, design and management of small (especially urban) water resources systems rely on the proper estimation of a design flood. A conventional approach is to ascertain the design rainfall intensity (or design storm hyetograph) from the available Intensity –Frequency – Duration (IFD) relationships developed for the region, and convert it to a corresponding flood hydrograph using a rainfall runoff model. However, the IFD based design storm poses uncertainty in the estimated flood as the influence of catchment antecedent conditions cannot be properly accounted for. Additionally, IFD relationships are typically developed using a single maximum rainfall event per year which may not necessarily translate to a corresponding annual maximum flow event for that year depending on catchment antecedent conditions. This non-consideration of antecedent conditions may subsequently lead to an underestimation of the design flood (Sharma and Srikanthan, 2006), especially for low return periods. For example, if the catchment is wet before a design event, the resulting flood will be greater than otherwise. Hence, an alternative to this design storm based approach is to use a continuous series of rainfall that can better reflect such antecedent characteristics. However, the existence of continuous rainfall data in reality is scarce due to the fact that its measurements are costly and time-consuming. To address this issue, previous studies have suggested the use of high resolution data generated from available low-resolution (daily) data through a data transformation procedure (Sivakumar and Sharma, 2008; Molnar and Burlando, 2005; Menabde et al., 1999)**.** A wide variety of models have been proposed in the literature to obtain fine temporal scale rainfall data from a coarser scale, namely from a daily to sub-daily level by way of rainfall disaggregation. Some common rainfall disaggregation models include Random Cascade Models based on scale invariance theory (Schertzer and Lovejoy, 1987; Olsson, 1998; Menabde and Sivapalan, 2000; Molnar and Burlando, 2005) as well as the Bartlett Lewis or Neyman Scott rectangular pulse models based on point process theory (Rodriguez -Iturbe et al., 1987).

Given that there are a host of possible disaggregation methods achieving the same objective (i.e. converting lower resolution rainfall to higher resolution rainfall) available in the literature with different theoretical underpinnings, it is useful to compare the results produced by different models in light of the application of different theory behind these models. As such, an attempt is made in the present study to evaluate the utility and suitability of different approaches for disaggregation of daily to sub-daily rainfall at a selected location. More specifically, we evaluate the performance of the canonical and micro canonical versions of the discrete multiplicative random cascades (Molnar and Burlando, 2005; Over and Gupta, 1994; Gupta and Waymire, 1993), the Randomized Bartlett Lewis Model (RBLM) (Koutsoyannis and Onof 2001), as well as the non-parametric method of fragments approach (MOF) (Sharma and Srikanthan, 2006), with each model assessed in the context of approximately daily to sub-daily rainfall disaggregation. Cascades based models are chosen for study here in light of the encouraging results earlier studies have reported (Molnar and Burlando, 2005; Koutsoyiannis and Mamassis, 2001), and also their appeal from a practical viewpoint because they are parameter parsimonious. The RBLM, being a widely applied stochastic rainfall generator, has also formed the basis for the development of other variants such as the Bartlett Lewis based hybrid model (Gyasi –Agyei and Willgoose, 1997, 1999) as well as power law tailed – autocorrelation downscaling method applied in conjunction with the RBLM (Marani and Zanetti, 2007). Lastly, the MOF is included to test the performance of a non-parametric model against its parametric counterparts. It is helpful to note that while the random cascades and method of fragments models have been exclusively used as ‘disaggregators’, the RBLM was initially formulated strictly as a rainfall simulator. The RBLM has since been modified and accorded an appropriate ‘adjusting procedure’ to enable it to be applied as a rainfall disaggregator (Koutsoyannis and Onof, 2001).

In this study, we choose our target disaggregation time step as hourly. As this study is primarily conducted to obtain fine resolution rainfall for the purposes of flood design, we are especially interested in statistics that are pertinent to this objective: i.e. how realistically the models simulate rainfall variability and intermittency, rainfall extremes, within-day wet spells, along with low order moment and autocorrelation characteristics. In addition, a measurement of the sensitivity of estimated parameters is conducted so as to assess the directions in which future improvements may be possible. The study is conducted using 86 years (1916 – 2001) of continuous hourly observed rainfall data from Observatory Hill, Sydney.

2. Random Multiplicative Cascades (RMC)

Multiplicative random cascade models originate from turbulence theory (Yaglom, 1966; Mandlebrot, 1974) and have been increasingly used in rainfall modelling in recent years (Menabde et al., 1997; Gupta and Waymire , 1993; Veneziano 2002; Molnar and Burlando, 2005). Although these models are purely phenomenological because the exact relationship between turbulence and rainfall remains unclear, their ability to reproduce observed structures in rainfall pattern analysis and its statistical properties have justified their continued application (Menabde et al., 1997). According to general multi-fractal theory, once fluctuations at a given scale are understood, those at other scales are deduced from scale invariance (via connecting a common thread through moments at different scales) and need not be independently specified. This study applies two versions of a larger group of models which operate based on the theory of scale invariance. These models are chosen due to good results reported in Molnar and Burlando (2005) when applied to temperate climate of Zurich, Switzerland. The section below summarizes the basic methodology of the models derived from previous studies (Gupta and Waymire, 1993; Over and Gupta, 1994, 1996; Molnar and Burlando, 2005).

2.1. Canonical Cascades

The canonical RMC model distributes rainfall on successive sub divisions (see Fig 1) with b as the branching number. As such, the ith interval after n levels of subdivision is denoted as Δ^i_n. The dimensionless scale is defined as $\lambda_n = b^{-n}$. The distribution of mass then occurs via a multiplicative process through all levels, 1...n of the cascade, such that the mass, μ_n , in sub division Δ^i_n is:

$$\mu_{(\Delta_n)^i} = r_0 \lambda_n \prod_{j-1}^{n} W_j(i) \quad for \ \ i = 1,2,\ldots b^n; \tag{1}$$

where, r_0 is the initial rainfall depth (in our case, daily rainfall) at n = 0, and $W_j(i)$ (hereafter denoted as just W for 'weights') is a range of weights that essentially forms the cascade generator (Molnar and Burlando, 2005). W is treated as an independent and identically distributed (iid) random variable, with the important condition that $E(W)$ = 0.5 so that mass is conserved, on average through all levels of the cascade. Properties of W can be estimated from the moment scaling function behaviour across all scales of interest. In particular, we need to obtain the rate of divergence/ convergence of moments with scale. For a random cascade, the ensemble moments have been shown to be a log- log linear function of the scale of resolution. The slope of this scaling relationship is known as the Mahane Kahane Pierre (MKP) function (Mandelbrot, 1974; Kahane and Pierre, 1976). Having identified the moment scaling function, an appropriate probability distribution for the weights can be specified (Over and Gupta, 1994, 1996; Molnar and Burlando, 2005). The intermittent lognormal - β model weights generator can be expressed as $W = BY,$ where B (the intermittency factor) controls intermittency in rainfall and Y controls rainfall amounts. In order to divide rainfall into rainy and non-rainy portions, the intermittent section of the model is based on the following probabilities derived according to the Bernoulli distribution:

$P(B = 0) = 1 - b^{-\beta} \ and \ P(B = b^{\beta}) = b^{-\beta}$ $P(B = 0) = 1 - b^{-\beta} \ and \ P(B = b^{\beta}) = b^{-\beta}$

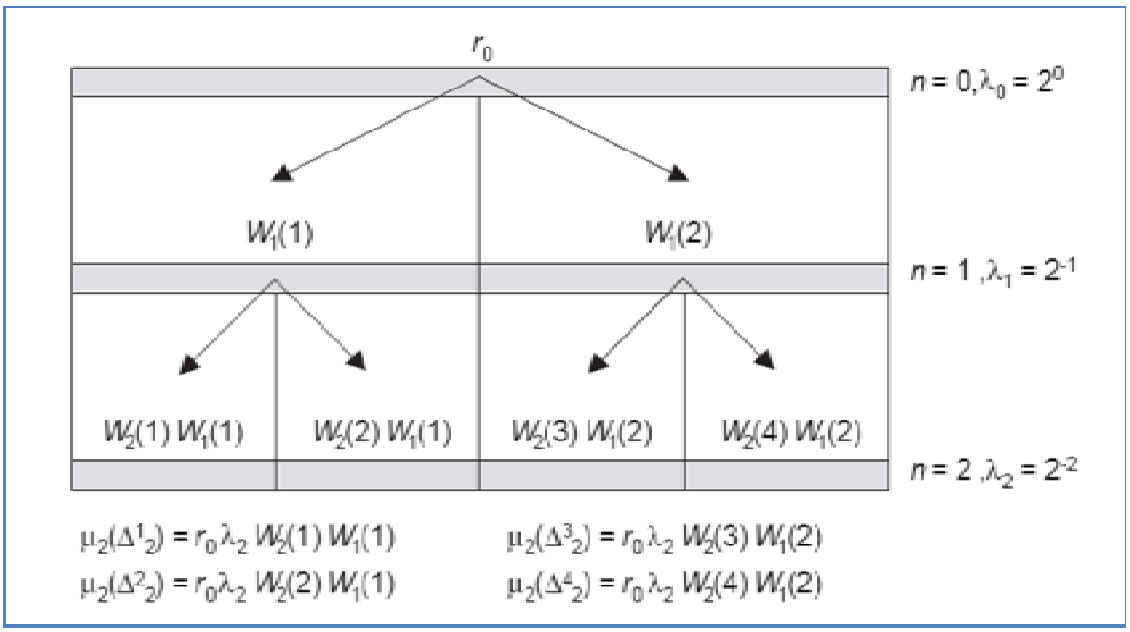
(2)

where β is the intermittency controlling parameter, B is the intermittency factor, and $E(B) = 1$. Variability in the positive part of the generator (i.e. where $B > 0$) is derived from the lognormal distribution, and is expressed as:

$$Y = b^{\left(\frac{-\sigma^2 lnb}{2} + \sigma X\right)}$$ $$Y = b^{\left(\frac{-\sigma^2 lnb}{2} + \sigma X\right)}$$

(3)

where X is a normal $N(0,1)$ random variable, σ^2 is the variance of Y, with $E(Y) = 1$. Note that a branching number $b = 24$ has been used in our study throughout, leading to a partial simulation of the observed autocorrelation structure in the disaggregated rainfall field through the induction of dependence from the higher level (daily time step) to the lower target cascade level (hourly time step).



generator W for
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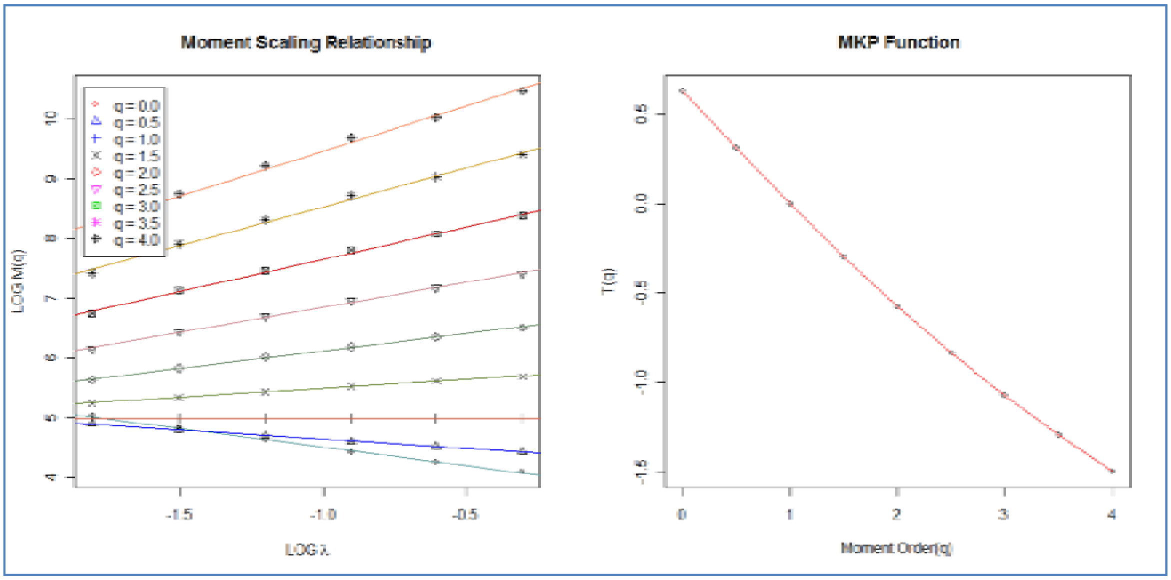
Parameter estimation of the canonical model is straightforward as only two parameters (β and σ^2) are required. Firstly, moments of order 0 to 4 are obtained for rainfall aggregated to time steps of 30 minutes to 1920 minutes. Note that the upper and lower limits are selected to encompass our origin (daily) and target (hourly) disaggregation level. A relationship between log (moment order) versus log (time scale) (see Fig 2) is then developed. The gradient of each fitted line is obtained via linear regression. These estimated gradients, $\tau(q)$, are subsequently plotted against moment order. To estimate the parameters, β and σ^2, the MKP function of W for the beta- lognormal model is then applied (Over and Gupta, 1994):

$$\tau(q) = (\beta - 1)(q - 1) + \frac{\sigma^2 lnb}{2}(q^2 - q)$$ $$\tau(q) = (\beta - 1)(q - 1) + \frac{\sigma^2 lnb}{2}(q^2 - q)$$

(4)

where $\tau(q)$ is the estimated gradient as defined above, q is the moment order. Optimization for the function in (4) is performed in the "*R - Project*" software which obtains nonlinear least-squares estimates of the parameters of the aforementioned MKP function. Optimised parameter estimates using the 86 year long Observatory Hill hourly rainfall record are shown in Table 1.



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2.2. Microcanonical Cascades

The micro canonical cascade model by definition conserves mass exactly at each cascade level. Hence, for a cascade with branching order (b) of two, the micro canonical weights (M) must either equal to a combination of [0, 1] when intermittency arises (hereafter intermittent part), or [M, 1-M], where 0 < M < 1 when there is no intermittency (hereafter variability part). The microcanonical cascade also differs from its canonical counterpart because its weights (M) are scale dependent and not independent and identically distributed (iid).

The intermittency parameter (p), and variability parameter (a) are estimated from the breakdown coefficients, which are defined as the ratio of rainfall of a random field averaged over different scales to account for decrease in variance with decrease in timescales (see Menabde and Sivapalan, 2000). More specifically, p represents the probability that one of the intervals in disaggregation is dry for scales between n and $n + 1$ and therefore is simply estimated from historical rainfall. a is estimated from the single parameter (symmetrical) *Beta* distribution (Molnar and Burlando, 2005):

$$f(M) = \frac{1}{B(a)} . M^{1-a} (1-M)^{1-a} \quad f(M) = \frac{1}{B(a)} . M^{1-a} (1-M)^{1-a}$$

(5)

where $B(a)$ is the *Beta* function with mean $E(M)$ = 0.5 and $Var(M) = 1/ (8(a +0.5))$. Since both a

and p have been known to be scale dependent (Menabde and Sivapalan, 2000), we have also fitted the scale dependent behavior of these parameters by power functions with scale (not shown here). Results for these parameters are also listed in Table 1.

Table 1: Parameter values for the Canonical and Microcanonical Cascades models. Note that while Canonical Model has constant parameters, the Microcanonical model parameters are time scale dependent. For example, Disaggregation Level 1,2…5 here corresponds to a timescale of 192 to 960 mins, 960 to 480 mins….. 120 to 60 mins.

Model Type	Parameters		
Canonical	β = 0.368 σ^2 = 0.0201		
Microcanonical	Disaggregation Level	Dry Probability '*p*'	Variability Parameter '*a*'
	1	0.647	0.445
	2	0.553	0.671
	3	0.473	0.918
	4	0.405	1.295
	5	0.346	1.387

2.3. Randomized Bartlett Lewis Model (RBLM)

The Bartlett Lewis Model (BLM) is a cluster-based model originally developed by Rodriguez-Iturbe et al. (1987) that represents rainfall events as clusters of rain cells where each cell is considered a pulse with a random duration and random intensity. The original BLM process is characterized by 5 parameters (λ, β, γ, η, μ_x) with the following description. The first parameter (λ) characterises the expected value of the Poisson distributed storm generation process. Each storm origin will generate a variable number of "storm cells" until a certain time from the storm origin is exceeded, at which time cell generation ceases (see Fig 3). The second parameter (β) represents the reciprocal of the expected value of another Poisson process representing the generation of additional cells in the storm (the first cell always coinciding with the start of the storm). The third parameter (γ) represents the reciprocal of the expected value of the storm generation duration which is characterised by an exponential distribution. In the original BLM, this time from the storm origin, often called the "generation duration" is taken to be exponentially distributed with an expected value of $1/\gamma$ where $\gamma = \varphi * \eta$, where φ is a dimensionless parameter. The duration of each cell's contribution is taken to be exponentially distributed with expected value *1/ η*. Although the *η* value was a constant in the original BLM, in the randomized version (RBLM), *η* are defined as independent and random for distinct storms (hence the name "randomized") following a gamma distribution with shape α and scale 1/ν. In the RBLM, the first cell is formulated to occur at the time of the storm origin, and additional cells are generated (until the generation duration is exceeded) as a second Poisson process with expected value β, where *β = κ * ν / φ*. As such, mean time between storm cells is *1/ β* and number of storm cells generated within generation duration has a mean of 1 + β/ γ. The intensity of each cell's contribution (or cell depth) is taken to be exponentially distributed with expected value $1/\mu_x$.

While the RBLM has been a widely applied rainfall generator, it has also been utilized for disaggregation, such as its use in conditional simulation in Glasbey et al. (1995), and by proportional adjusting as in Onof and Koutsoyannis (2001). The adjusting procedure modifies the initially generated values ($\widetilde{X_s}$ $\widetilde{X_s}$) at a lower time step from a RBLM to obtain adjusted values (X_s)

$$X_s = \widetilde{X_s}\left(\frac{Z}{\sum_{j=1}^{k}\widetilde{X_j}}\right) \quad (s = 1, \ldots, k)$$

$$X_s = \widetilde{X_s}\left(\frac{Z}{\sum_{j-1}^{k}\widetilde{X_j}}\right) \quad (s = 1, \ldots, k)$$

(6)

where *Z* is the higher-level variable (i.e. observed daily rainfall in this case) and *k* is the number of lower-level variables within one higher-level period, which for example may typically be daily rainfall, or a wet spell that continues for several days (Koutsoyiannis 1996; Koutsoyannis and Onof, 2001).Given that rainfall depths in rainy intervals can be assumed to be approximately gamma distributed, the proportional adjusting procedure is deemed appropriate. Nevertheless, some bias may be introduced. This bias has been addressed by the use of a repetitive scheme, generating Bartlett Lewis sequences until the difference between simulated and observed daily totals is less than a pre-set value of *d* as defined below:

$$d = \left(\sum_{i=1}^{L} ln^2\left[\frac{Z_i + c}{\tilde{Z}_i + c}\right]\right)^{0.5}$$

$$d = \left(\sum_{i=1}^{L} ln^2\left[\frac{Z_i + c}{\tilde{Z}_i + c}\right]\right)^{0.5}$$

(7)

With reference to (7), the pre-set value, *d*, helps to reduce bias through firstly employing a logarithmic distance such that extreme values are not associated with undue weight, and similarly, that the constant "*c*" is introduced to avoid domination by very low values. *L* is the sequence of wet days generated while *Z* values are the historical (numerator) and generated (denominator) daily depths of day *i*. In this study, the value of *d* is set to unity as the maximum allowable distance to avoid unacceptable bias. The detailed algorithm for coupling of the RBLM with the adjusting procedure is set out in Koutsoyiannis and Onof (2001).

The parameters for RBLM are estimated on a monthly basis, assuming local stationarity within the month (Bo et al., 1994) using the method of moments. The set of parameters to be fitted is given by the set Θ, where Θ = {λ, μx, κ, φ, α, v}. The second-order properties of the accumulated process over the time interval, T, which represent selected statistical attributes of the rainfall time series (Rodriguez-Iturbe et al., 1987), are estimated over varying levels of aggregation (1 hour to 48 hours). In this study, twelve statistical attributes (mean, variance, lag-1- auto-covariance and dry proportion at the 1HR, 24HR and 48 HR aggregation scale) are used to ascertain parameters, as recommended by Koutsoyiannis (2000) using an objective function that sought to minimise the weighted sum of squared deviation of observed and modelled attributes. The optimised parameter values for each month are shown in Table 2. The 'R-Project' software is used to ascertain optimal parameters using the above objective function. Problems of parameter instability of the RBLM model have been reported in several previous studies (Onof and Wheater 1993; Khaliq and Cunnane 1996). The instability of parameters that control storm generation duration (φ, α, and v), would result in the frequent generation of storms of excessively long durations, which are physically not feasible. While the literature contains suggestions of alternate optimisation algorithms to circumvent this difficulty (Onof and Wheater, 1993), we address this issue in our paper by imposing a constraint on the maximum storm

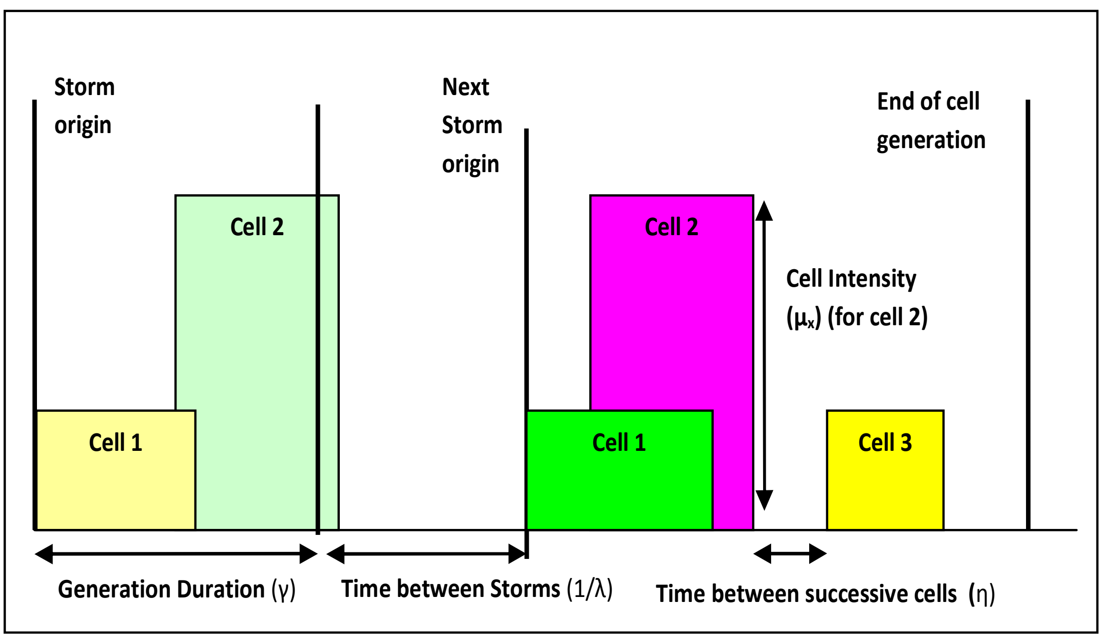

Figure 3: Schematic showing RBLM process. Storm arrivals follow Poisson process with mean of 1/ λ, with generation duration of each storm exponentially distributed with mean 1/ γ . First cell is fixed to occur at storm origin while later cells within a storm arrive by a second Poisson process with expected value of β. Duration of each cell is exponentially distributed with mean of 1/ η. Each cell's intensity is exponentially distributed with a mean of μ_x .

length which is assessed from the historical record by assuming storms to be separated by at least 5 consecutive hours of zero rainfall. These constraints (see Table 3) help stabilize the parameters to a large extent and prevent the trawling of 'useless' parameter space, while being flexible enough to allow for the possibility of a varying number of acceptable parameter combinations.

Table 2: RBLM parameters estimated on monthly scale. Some of these parameters (φ, α, and v) were constrained to prevent the trawling of 'useless' parameter space and help avoid local optima during the minimization computations.

Parameter /Month	λ (hr^{-1})	$\kappa = \beta/\eta$	$\varphi = \gamma/\eta$	α	v (hr^{-1})	μ_X (hr^{-1})
JAN	0.014	1.367	0.100	2.267	0.221	4.167
FEB	0.014	0.361	0.042	2.014	0.161	6.720
MAR	0.015	0.466	0.049	2.153	0.174	7.130
APRIL	0.013	0.677	0.035	2.162	0.129	5.602
MAY	0.012	0.454	0.022	2.147	0.096	6.427
JUN	0.011	0.235	0.010	1.923	0.094	5.907
JULY	0.009	0.752	0.009	2.179	0.029	5.833
AUG	0.009	0.732	0.012	1.958	0.030	6.420
SEP	0.013	0.311	0.088	2.420	0.567	5.796
OCT	0.013	0.311	0.088	2.420	0.567	5.796
NOV	0.016	1.205	0.055	1.971	0.047	6.524
DEC	0.012	0.197	0.032	2.636	0.324	5.835

Table 3: Upper and Lower Limits of constraints applied to selected RBLM parameters

Parameter	Upper Limit	Lower Limit
φ	0.10	0.01
α	10.0	1.00
v (hr^{-1})	10.0	0.01

2.4. Method of Fragments (MOF)

This method stands in contrast to the RBLM and Cascades models as it is non-parametric. As such, it makes no major assumptions about the nature of the relationship between continuous and aggregate rainfall. The MOF generates sequences of rainfall that exhibit persistence attributes similar to those observed by maintaining temporal dependence at a daily time scale, and then using a nonparametric disaggregation logic to impart dependence to sub-daily time steps (Sharma and Srikanthan, 2006). The methodology of MOF reflects how it represents daily temporal dependence by using high frequency rainfall predictors and longer term attributes such that distributional and seasonality characteristics. This is done by way of resampling a vector of fragments representing the ratio of the sub-daily to daily rainfall. Resampling is performed by via a modified *K*-nearest neighbour algorithm (Sharma and Srikanthan, 2006; Lall and Sharma, 1996) on the basis of the two criteria as set out below:

- 'Within day' fractions are sampled from an 'observational window' that spans 15 days on either side of our day of interest. This would increase the sample size available for sampling purposes and also account for effects of seasonality. For example, if we want to disaggregate daily rainfall on 15th Jan of our daily time series, we look into entire month of January (1-30) across the full observed record to find the nearest neighbor with reference to the daily rainfall total being disaggregated.

- The observational window is further narrowed by isolating days that coincide with the 'wetness state' associated with the current day, this state (representing the rainfall occurrence across three consecutive days) being one of the following:

    - *wet – **wet** – wet*
    - *dry – **wet** – dry*
    - *wet – **wet** –dry*
    - *dry – **wet** – wet*

This second criterion is especially important because it helps to identify whether our 'wet' day of interest lies at the start, the end or in the middle of a storm. As such, our 'selected' day from history is expected to be accorded with a more realistic distribution, compatible with our 'wet' day of interest. The MOF further aims to appropriately represent characteristics in generated sub-daily sequences by ensuring that disaggregated sub-daily rainfall from model output sum up to the daily rainfall and that the model is sensitive to various sub-daily temporal patterns that shift with time of the year, and also the magnitude of daily rainfall. The above conditions are reflected by its generation procedure, which operates under the assumption that daily rainfall values to be disaggregated are representative of daily rainfall formed by disaggregating observed continuous rainfall time series, and that sub-daily fractions represents temporal pattern applicable at for the site (Sharma and Srikanthan, 2006).

3. Results

The entire historical rainfall record is used to calibrate the models (where parameters are used). Historical daily rainfall for the same record is then disaggregated to hourly rainfall, with a total of 10 realizations performed. The RBLM is run using the HYETOS program (Koutsoyiannis, 2000), while software for the other methods are developed by the authors. The following sub-sections present the performance of each model with respect to their ability to simulate standard statistics such as mean, variance, lag-1- auto covariance and dry proportions, as well as other statistics important for design flood purposes such as wet spell lengths, their distribution and IFD relationships.

3.1. Simulation of Low Order Moment Statistics

All the models reproduced the mean hourly rainfall well (see Table 4). However, the microcanonical model overestimated hourly variance by a large margin. It is contended here that this may be due to the poor fit of beta distribution to Sydney rainfall data. Figure 4 illustrates the probability density plot of observed and generated breakdown coefficients (which are essentially cascade weights from scale *n* to *n + 1*) for Sydney rainfall for the disaggregation time steps. As noted in the microcanonical model description, the breakdown coefficients are used for estimating the 'variability' parameter *a* for non intermittent weights ($0<W<1$). Importantly, the single parameter beta distribution is neither able to simulate the decreasing variance as we proceed to finer disaggregation levels, nor capture the pronounced 'spike' in the high number of cascade weights that are distributed between 0.4 and 0.6 (thus indicating low rainfall variability) especially at the finest of disaggregation levels of 120 - 60mins and beyond (see Fig 4).

The canonical cascades model slightly underestimates hourly variance albeit overestimating the variance of the aggregated hourly rainfall at daily level. This may be attributed to the fact that, while being parameter parsimonious, the parameters that control both rainfall variability, (σ^2) and intermittency, (β) show fluctuations at both yearly as well as monthly time scales. Taking monthly β for instance, a lower β value would correspond to less frequent intermittent rainfall, which is representative of winter rainfall in Sydney dominated by frontal storms. A higher β value reflects greater chance of intermittency, which is consistent with higher occurrences of convective type rainfall during the hot summer months. Similarly, a lower (higher) σ^2 value reflects lower (higher) rainfall variability, which is representative of the contrasting dominant rainfall mechanisms that operate during winter and summer months.

By using over-arching parameters to encompass all years, there may have been a significant variance trade-off in favour of bias, resulting in the intangibility of the canonical model to capture both seasonal and other longer term rainfall attributes, thus possibly resulting in errors introduced in the estimation of variance (see Figure 5). In addition, the inherent canonical model structure which does not preserve rainfall mass exactly at each disaggregation level explains the inflated variance when disaggregated hourly rainfall is aggregated to a daily time scale. The MOF and RBLM models performed well in reproducing standard statistics at both hourly and daily time scale.

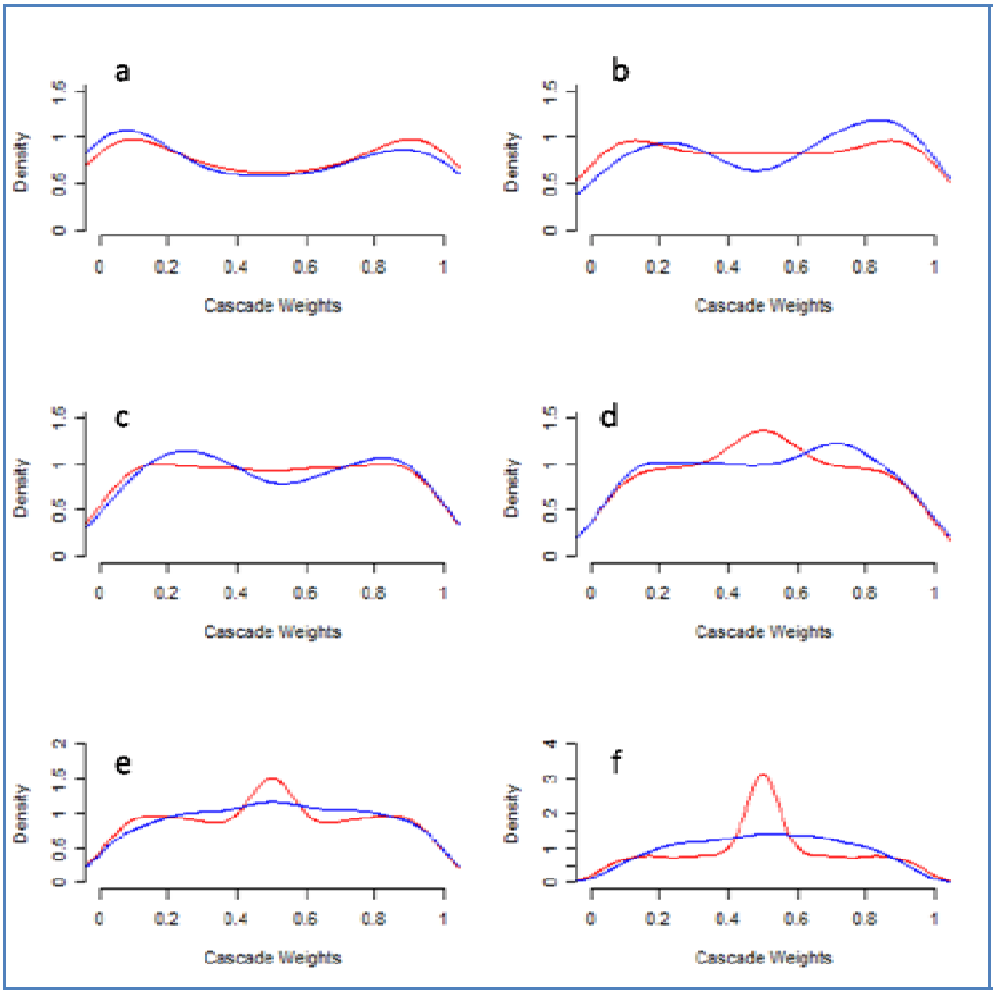

Figure 4: Probability density plot of breakdown coefficients (which are essentially observed cascade weights (0<W<1) from cascade level *n* to *n + 1*) (shown in red) and generated weights from the beta distribution (shown in blue) Cascade levels shown are (a) 1920-960mins, (b) 960- 480mins, (c) 480-240mins, (d) 240-120mins, (e) 120-60mins, (f) 60-30mins. Note decreasing variance from higher to lower cascade levels (a) – (f).

Table 4: RBLM parameters estimated on monthly scale. Some of these parameters (*φ, α, and v*) were constrained to prevent the trawling of 'useless' parameter space and help avoid local optima during the minimization computations. Notation in bold highlights statistics that were not well simulated by the models

Model	Mean		Variance		lag-1-autocovariance		Dry Proportion	
	1HR	24HR	1HR	24HR	1HR	24HR	1HR	24HR
OBS	0.128	3.06	0.883	114.23	0.525	0.311	0.912	0.673
RBLM	0.127	3.06	0.871	113.98	0.575	0.310	0.954	0.673
MOF	0.127	3.06	0.907	114.03	0.484	0.310	0.913	0.674
CANON	0.128	3.07	**0.842**	**135.22**	0.238	0.267	0.894	0.673
MICRO	0.128	3.06	**2.398**	116.56	**0.116**	0.248	0.913	**0.612**

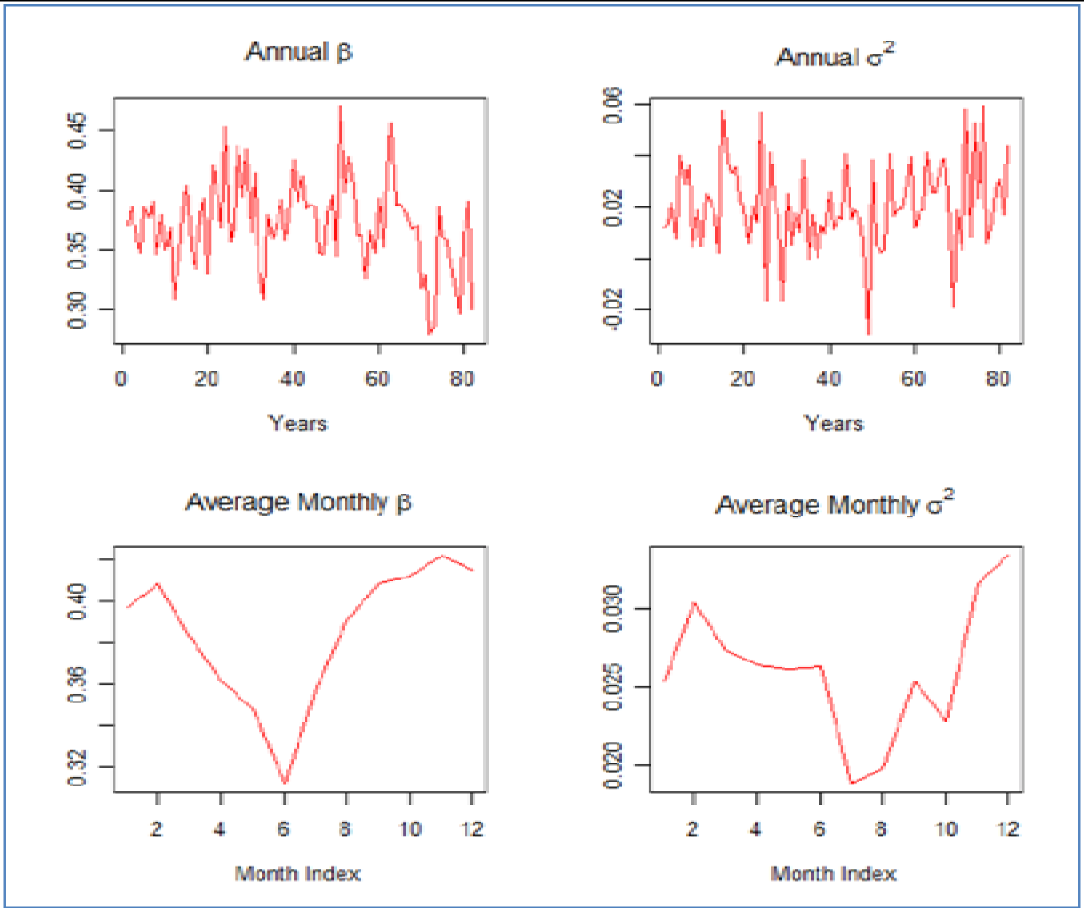

Figure 5: Parameters of the canonical model estimated on an annual and monthly basis. Note that the use of a single set of parameters fitted to the entire rainfall record therefore does not account for inter annual and seasonal fluctuations.

3.2. Assessment of Extremes

There are several ways of extracting extreme value information from available rainfall time series. The most straightforward and widely used approach selects the annual maxima. Frequency analysis of the resulting annual maximum series then provides an average range of application in terms of the return period from 1 to 1000 years (Verhoest et al., 1997). Here, IFD curves for the 1 and 24 hour durations are constructed based on empirical cumulative distribution of the rainfall series from observed and disaggregated rainfall series. For this procedure, annual maximum rainfall is ranked from highest to lowest, and empirical estimates of the annual exceedence probability (AEP) is estimated according to:

$$\mathrm{AEP}(m) = (m - 0.4) / (N + 0.2) \qquad (8)$$

where m is the rank and N is the length of record (Pilgrim and Doran, Australian Rainfall and Runoff, 1987) These AEP's are then plotted against corresponding log-transformed rainfall intensities (see Fig 6) representing the IFD relationship for Sydney. For the 1HR duration case, the MOF model most closely reproduces the observed IFD, which is to be expected since it disaggregates by way of resampling fractions of observed rainfall and assuming that it picks up the days having observed maximum hourly rainfall during the resampling process. Both the canonical and RBLM models underestimate the hourly empirical IFD. The RBLM in particular significantly underestimates extreme rainfall at low return periods while the canonical model empirical IFD curve diverges from that of the observed at high ARIs, indicating that it underestimates the less frequent, large rainfall events which are important from a flood design perspective. The microcanonical model overestimates extreme rainfall at all AEPs by a significant margin which is consistent with the earlier results that the model provides an inflated variance of the disaggregated hourly data. With regards to the 24HR intensities, all models converge approximately to the observed intensity-frequency relationship. While one would expect the models that retain total rainfall mass exactly during disaggregation (such as the RBLM, MOF and Microcanonical models) to replicate the observed 24HR empirical IFD, this is not case. This is caused by the simple fact that the aggregation process is not constrained to be 'within day'. This is based on the assumption that rainy intervals are allowed to occur at random when disaggregating intermittent (0,1) occurrences: i.e. two consecutive rainfall time steps could result in 4 possibilities: 1010, 0101, 1001, 0110, thus, fundamentally altering the aggregation properties of rainfall despite having conserved actual rainfall 'mass'. Therefore, the maximum disaggregated 24 hour 'spell' could theoretically occur over more than one calendar day.

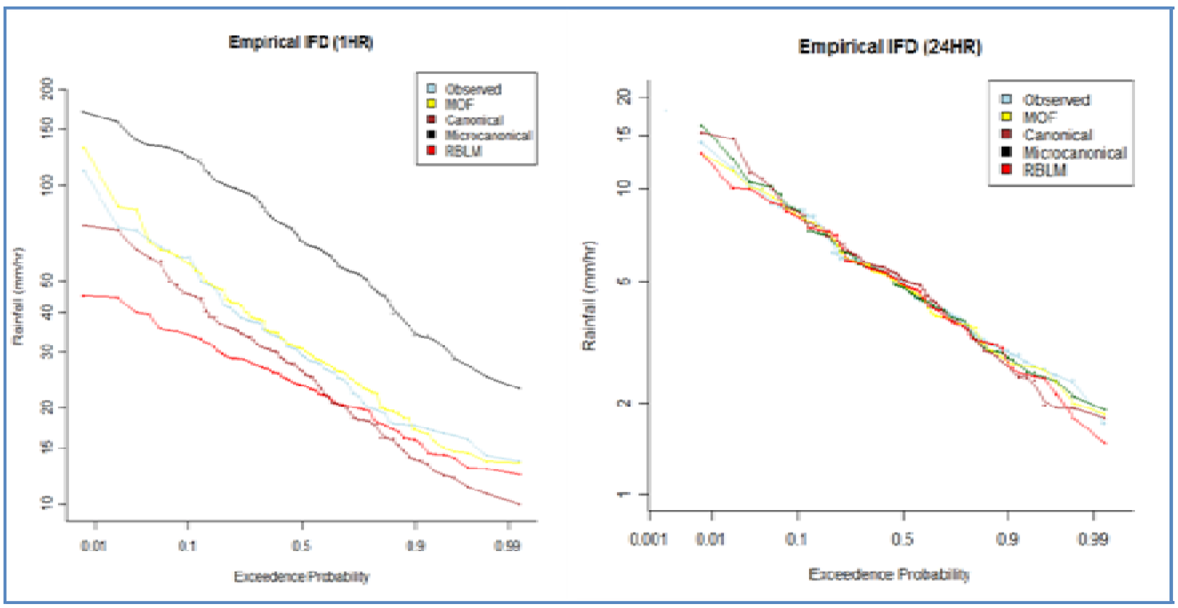

Figure 6: 1 and 24HR Empirical IFD curves for observed rainfall and disaggregated rainfall by the models.

3.3 Wet Spells

This study has also investigated the ability of models to reproduce wet spells that are similar to that of observed rainfall. The generation of realistic wet spells is important from a design flood perspective because rainfall intermittency and persistence need to be quantified to gauge antecedent catchment soil conditions. This cannot be achieved simply by an undertaking an IFD analysis of extreme values. For purposes of this study, a wet spell is defined by consecutive hours of rainfall within a rainy day, in accordance with previous literature (Llasat, 2001; Menabde and Sivapalan, 2000).

The MOF model best captures observed within day wet spell properties of interest such as the mean spell length per day (an average of all spells of different lengths occurring within a day) and mean number of spell occurrences per day. This is reflected by its ability to match the proportions of observed short, medium and long wet spells (see Table 5 and Fig 7). Both versions of cascades models underestimate wet spell lengths. The canonical model in particular fails to generate within day wet spells longer than four hours suggesting that it poorly simulates rainfall persistence. This may be caused by the inherent model structure which does not require cascade weights to be conserved at each time step, thus resulting in possibility of generating physically unrealistic exclusively zero rainfall values at scale $n + 1$ although rainfall did occur at scale n.

Table 5: Proportion of Within Day Wet Spell lengths estimated from observed and disaggregated rainfall. Short, medium and long spells encompass wet spells of 1-2, 3-4 and greater than 4 hours in length respectively.

	Short Spells	Medium Spells	Long Spells
OBS	0.548	0.222	0.230
MOF	0.549	0.225	0.226
CANON	0.912	0.081	0.008
MICRO	0.805	0.159	0.035
RBLM	0.658	0.201	0.141

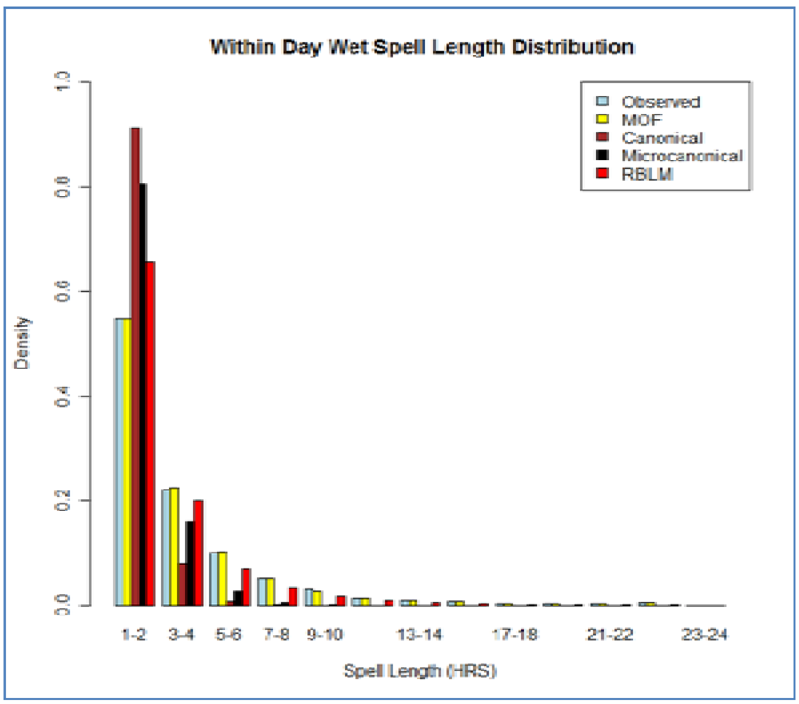

Figure 7: Within Day Wet Spell Distribution for disaggregation models compared to observed wet spells.

4. Concluding Remarks

This paper has evaluated the performance of some widely known daily rainfall disaggregators such as the RBLM, two versions of the random cascades model and MOF model using continuous rainfall data of Sydney. In particular, the models are gauged in the areas of simulation of standard rainfall statistics, extreme values and reproduction of wet spells. In terms of reproduction of observed statistics, the MOF model outperforms the other models. This is not entirely unexpected given that the MOF logic operates based on resampling of observed rainfall fractions (at sub-daily time scale) and is therefore expected to produce statistics that bear the closest resemblance to observed data. The strength of this model, however, may also serve as a limitation because its applicability is confined to areas where continuous sub daily data is available. Also, the MOF is not flexible enough to simulate events beyond the limits of the historical record. As a result, without conditioning the MOF model on synthetic rainfall data representative of a future climate, it may not be able to factor the effects of climate change during the disaggregation process. In the same vein, this argument holds true for the other models since their parameters were estimated based on observed historical rainfall only, followed by the assumption that these parameters remain valid for the future. However, it may be easier to condition the parameters based on climate change factors should these factors be ascertained.

On a whole, the RBLM performs better than the cascade models albeit with a slightly inflated simulation of dry proportions at an hourly scale as well as an underestimation of extreme rainfall at low return periods. However, the model is not easy to be parameterised and the choice of statistics (and the time scales at which these statistics are gauged) remains subjective. Another concern is that model parameters may not necessarily represent actual physical quantities because they depend on the time scale that is chosen for fitting (Foufoula- Georgiou and Guttorp, 1986), resulting in the use of an intuitive parameter constraining procedure to ensure that somewhat realistic quantities are produced. The selection of the value for the pre –set value *d* for the adjusting procedure is also somewhat arbitrary, with lower *d* values vastly increasing the number of iterations required to obtain close enough rainfall cell amounts match observed rainfall. This results in increased computation time, and occasionally created ‘blocks’ (computer running out of memory) whereby the maximum number of iterations are reached but HYETOS is still unable to match up daily totals between disaggregated and observed data.

The scaling models, in particular the micro canonical model, did not outperform its simpler counterpart (the canonical model) when applied to Sydney rainfall. Since the canonical model is parameter parsimonious, its performance is judged to be relatively satisfactory considering its simplicity. However, the micro canonical model performed poorly by generating inflated hourly rainfall variance and consequent overestimate of extreme rainfall at the same time step. This is primarily attributed to the inappropriate choice of the beta distribution to Sydney rainfall, therefore highlighting the importance of selecting an appropriate probability distribution considering that the model is wholly reliant on cascade weights. For example, perhaps the beta distribution may have been appropriate for the temperate, alpine Swiss rainfall (Molnar and Burlando, 2005) but is ill suited to Sydney’s Mediterranean, coastal climate. Other factors that may have affected the performance of the cascades models in general include the fact that physically different mechanisms (i.e. contrast between temporal distribution of convective and frontal rainfall) are unlikely to be simply the result of drastically different realizations of the same parameters as well the effect of longer term persistence. With reference to Fig 5 in the section 3.1 above, parameter uncertainty could have arisen from the failure to account for longer term, low frequency modes that influence South East Australian rainfall such as El- Nino Southern Oscillation, Indian Ocean Dipole and Interdecadal Pacific Oscillation type events as well as seasonality. Lastly, there could be the possibility of imperfect scaling behaviour (Veneziano et. al, 2006), i.e. that multi scaling behaviour may not be present within our time scales of interest – from a daily to hourly time step. According to Veneziano et al (2006), while it is widely accepted that rainfall inherits its scaling properties from atmospheric turbulence, the detailed transfer of multifractality from turbulence to rainfall remains unclear. In particular, rainfall may violate scale invariance even if atmospheric turbulence is perfectly multi-fractal, as found by spectral analyses of rainfall times series (Olsson, 1995).

With the advent of climate change, we believe that discerning the relative weaknesses and strengths of each model is important as in future there is greater possibility of wider applications of the disaggregation methods to downscaled daily rainfall for proper assessment of the changes in the occurrence and frequency of extreme rainfall events in a changed climate . As such, information regarding the performance of the models is expected to guide hydrologists in applying daily to sub-daily 'disaggregators' with greater insight. We intend to focus future research on addressing the issues raised in this paper especially with regards to the cascades models, as well as extend analyses to other point locations (i.e. coastal versus inland) to discern the relative impact of local topography and large scale forcings on model parameters.

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References

Foufoula-Georgiou, E. and P. Guttorp, 1986. Compatibility of continuous rainfall occurrence models with discrete rainfall observations**,** Water Resources Res. 22(8), 1316-1322

Glasbey, C.A., Cooper, G., McGechan, M.B., 1995. Disaggregation of daily rainfall by conditional simulation from a point-process model. J. Hydrol 165, 1–9.

Gupta, V.K. and Waymire, E.C., 1993. A statistical analysis of mesoscale rainfall as a random cascade. J. Appl. Meteorol. 32, 251– 267.

Gyasi-Agyei, Y., and Willgoose, G.R., 1997. A hybrid model for point rainfall modelling. Water Resources Res. 33 (7), 1699–1706.

Gyasi-Agyei, Y. and Willgoose, G.R., 1999. Generalisation of a hybrid model for point rainfall. J. Hydrol. 219 (3–4), 218–224.

Pilgrim, D.H., and Doran, D.G., Australian Rainfall and Runoff - A Guide to Flood Estimation , Revised Edition, Institution of Engineers, Australia, 1987

Khaliq, M.N. and Cunnane, C., 1996. Modelling point rainfall occurrences with the modified Bartlett–Lewis rectangular pulses model. J. Hydrol. 180, 109–138.

Koutsoyannis,D. and N. Mamassis, 2001: On the representation of hyetograph characteristics by stochastic rainfall models. J. Hydrol. 251, 65-87

Koutsoyiannis, D. and Onof, C., 2001. Rainfall disaggregation using adjusting procedures on a Poisson cluster model. J. Hydrol. 246, 109–122.

Koutsoyiannis, D. and Onof, C., 2000. A computer program for temporal rainfall disaggregation using adjusting procedures. XXV General Assembly of European Geophysical Society, Nice, Geophysical Research Abstracts, 2

Kahane, J.P., and Peyriere, J., 1976. Sur certaines mertingales de Benoit Mandelbrot. Adv. Math. 22, 131–145.

Lall, U. and Sharma, A., 1996. A nearest neighbor bootstrap for time series resampling. Water Resources Res, 32(3): 679-693.

Llasat M. C, 2001. An objective classification of rainfall events on the basis of their convective features, Application to rainfall intensity in the North-East of Spain, International Journal of Climatology, 21, 1385–1400

Mandelbrot, B.B., 1974. Intermittent turbulence in self-similar cascades: divergence of high moments and dimension of the carrier. J. Fluid Mech. 62, 331– 358

Marani, M., and S. Zanetti, 2007. Downscaling rainfall temporal variability, *Water Resources Res.*, *43*

Menabde, M., Sivapalan, M., 2000. Modeling of rainfall time series and extremes using the bounded random cascades and Levy-stable distributions. Water Resources Res. 36 (11), 3293–3300.

Menabde, M., Seed, A., Pegram, G., 1999. A simple scaling model for extreme rainfall. Water Resources Res. 35 (1), 335– 339.

Menabde, M., Harris, D., Seed, A., Austin, G., Stow, D., 1997. Multiscaling properties of rainfall and bounded random cascades. Water Resour. Res. 33 (12), 2823– 2830.

Molnar, P., Burlando, P., 2005. Preservation of rainfall properties in stochastic disaggregation by a simple random cascade model. Atmos. Res. 77, 137–151.

Olsson J. 1995. Limits and characteristics of the multifractal behavior of a high-resolution rainfall time-series. Nonlinear Processes in Geophysics 2: 23–29.

Onof, C., Wheater, H.S., 1993. Modelling of British rainfall using a random parameter Bartlett–Lewis rectangular pulse model. J. Hydrol. 149, 67–95.

Over, T.M., Gupta, V.K., 1994. Statistical analysis of mesoscale rainfall: dependence of a random cascade generator on large scale forcing. J. Appl. Meteorol. 33, 1526–1542.

Rodriguez-Iturbe, I., Cox, D.R., Isham, V., 1987a. Some models for rainfall based on stochastic point processes. Proceedings of the Royal Society of London A 410, 269–288.

Sharma, A., Srikanthan.R, 2006. Continuous Rainfall Simulation: A Nonparametric Alternative, 30th Hydrology and Water Resources Symposium 4 - 7 December 2006, Launceston, Tasmania

Sivakumar, B. and Sharma, A., 2008. A cascade approach to continuous rainfall generation at point locations. Stochastic Environmental Research and Risk Assessment (SERRA): 1-9.

Veneziano, D. ,2002. Large deviations of multifractal measures. Fractals 10 (1), 117–129.
Veneziano, D.,P. Furcolo, et al. 2006. "Imperfect scaling of time and space-time rainfall." J. Hydrol. 322(1-4): 105-119.

Verhoest N, Troch P, Troch F.D, 1997. On the applicability of Bartlett–Lewis rectangular pulses models in the modelling of design storms at a point. J. Hydrol. 202, 108–120

Yaglom, A. M., 1966. The influence of fluctuations in energy dissipation on the shape of turbulence characteristics in the inertial interval, Sov. Phys. Dokl., Engl. Transl., 11, 26–29

Appendix 2: "Addressing Climatic Non-Stationarity in the Assessment of Flood Risk"

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Abstract

Present day flood estimation practise is underpinned by the assumption that flood risk in a future climate will reflect historical flood risk as represented by the instrumental record. This assumption, which is commonly referred to as the assumption of stationarity, recently has been questioned as a result of both an increased appreciation of the natural variability in our hydroclimate at temporal scales beyond that of the instrumental record, as well as the projected intensification of the hydrologic cycle due to anthropogenic climate change. These developments have led some authors to suggest that the stationarity assumption should henceforth be considered invalid, thereby calling into question all the methods that are underpinned by it, including flood frequency analysis using observed streamflow records and rainfall-runoff modelling informed by instrumental precipitation and streamflow records.

In this paper we review a wide range of possible sources of non-stationarity in the Australian climate record, and highlight that the primary sources of non-stationarity relevant for flood risk assessments include natural climate modes that vary at timescales similar to the length of the instrumental record, as well as long-term trends and step changes that are attributable to anthropogenic climate change. Although prescriptive guidelines that describe how to address this non-stationarity are currently unavailable in Australia, this review nonetheless highlights the importance of using long records for flood analysis, possibly by extending records using nearby stations. Furthermore, it will become increasingly necessarily to develop plausible estimates of how the climate will evolve, and we describe some climate modelling tools which allow for the development of future climate scenarios. Finally, we emphasise that removing the assumption of stationarity will inevitably result in an increase in the uncertainty associated with future flood estimates, and suggest that may require new methods to conceptualise and manage future flood risk.

1. Introduction

The field of flood hydrology is concerned with the reconciliation of the seemingly random behaviour of weather patterns with the need to provide fixed flood estimates of a desired exceedance probability for use in planning and engineering design. To this end, it is often assumed that although weather varies randomly from one day to the next, the long-term climate can be viewed as a stationary process, such that the statistics (including both averages and extremes) derived from the instrumental record can be assumed to remain valid for any future period of interest. This has formed the basis for most methods currently used in the quantification of flood risk, including flood frequency analysis based on historical stream flow records for cases where sufficiently long records are available and the catchment has not exhibited significant changes such as urbanisation, as well as the use of rainfall-runoff models informed by the instrumental precipitation record (e.g. see I.E. Aust, 1997).

The assumption of climate stationarity has always been questionable, although the implications of small amounts of climate variability and change usually have been perceived as negligible, particularly when viewed within the context of other sources of uncertainty such as that due to short instrumental records, measurement biases and modelling errors (Milly *et al*, 2008). Nevertheless, recent research into low-frequency 'natural' climate fluctuations has shown that the instrumental record is often inadequate to capture the full bounds of climate variability (Jain and Lall, 2001). Anthropogenic climate change resulting from historic and projected greenhouse gas emissions is also expected to push the climate outside the envelope of variability implied by the instrumental record, leading numerous researchers to proclaim that the assumption of stationarity 'is dead' (Milly *et al*, 2008).

Although the limitations of stationarity are easy to identify, the transition from a stationarity to a non-stationarity framework in hydrology is likely to prove considerably more complex. In particular, if the instrumental record does not mirror what is likely to occur in the future, how does one estimate future flood risk? The purpose of this paper is to attempt to address this question, with a view to assisting practitioners of hydrology to better account for natural climate variability and anthropogenic climate change in flood estimation. Specifically, we seek to answer the questions: what are the dominant sources of non-stationarity in our climate system, and to what extent are they likely to bias future flood estimates? What tools are available to quantify future precipitation intensity? What confidence can be ascribed to climate change projections, and what means are there of reducing this uncertainty? And finally – given the significant increase in uncertainty associated with the shift to a non-stationary approach – is it time to change the way in which we conceptualise and manage flood risk?

In the next section, we describe an idealised approach to representing non-stationarity, and emphasise that the optimal flood estimation approach will require both a diagnosis of the sources and behaviour of non-stationary influences in the instrumental record, and an estimate (or projection) of how such influences will evolve in the future. To this end, a brief overview of recent developments in climate science is given in Section 3, with a focus on observations and projections associated with flood-producing precipitation events. Other climate variables influencing flood risk, including mean annual rainfall and potential evapotranspiration affecting antecedent moisture conditions, sea level pressure and wind speed and direction affecting storm surge, and sea level rise (CSIRO, 2007; IPCC, 2007), are not considered explicitly in this paper although many of the issues raised are more broadly applicable. Finally in Section 4 we provide conclusions and discuss broader implications associated with the shift to a non-stationarity approach in flood estimation.

2. Understanding non-stationarity: oscillations, trends and step changes.

As suggested in the introduction, the transition from a stationary to a non-stationary framework requires both a diagnostics component, in which the nature of non-stationarity in the data of interest is identified, and the development of a plausible set of assumptions or 'projections' about how the drivers of non-stationarity are expected to evolve in the future. To elucidate these concepts further, we present an idealised example of the types of non-stationarity that might exist in our climate data, and the implications of each on the estimation of future flood risk. This example is presented in **Figure 1**, and was derived by randomly generating a time series of length 100, which can be considered analogous to a hydrologic time series such as mean annual rainfall, maximum annual rainfall or stream flow over the 20th century.

We begin with the stationary situation in **Figure 1a**, which as discussed previously represents the situation assumed in most flood estimation approaches. The appeal of the assumption is obvious – to estimate the event which has a 1% chance being exceeded in any given year (henceforth referred to as the 1 in 100 Annual Exceedance Probability event), one simply needs to determine the underlying probability distribution (for example the normal, generalised extreme value or log-Pearson type 3) and then compute the magnitude of the event which is exceeded on average 1% of years.

The sequence in **Figure 1b** was developed as the supposition of the stationary series in **Figure 1a** with a lower-frequency cyclical component. This can be considered analogous to the implication of natural modes of climate variability such as the El Niño Southern Oscillation (ENSO) phenomenon, which are known to vary at a frequency of between 3 and 7 years (Goddard *et al*, 2001). The unconditional probability density function, which is simply the probability density function estimated from the full instrumental record, is presented on the right panel as a black solid line. We propose that this sequence can be considered to be effectively stationary, in the sense that the next 100 years of data will tend to have the same statistics as the observational data, so that one can extract various statistics such as the mean or the 1 in 100 AEP event in a similar manner to the first example. Nevertheless, if one is able to project the future evolution of the underlying low-frequency climate mode, such as is possible with the ENSO phenomenon by up to several seasons ahead (Goddard *et al*, 2001), then one can provide better (in the sense of lower variance) near-term estimates of flood risk. This is illustrated in our example (right panel, black dashed line) where we forecast that the climate mode will shift to the positive phase in the short-term future, and then estimate the conditional flood risk by only including in our sample those flood records associated with the positive phase of the climate mode. Such conditional, or time-constrained, flood estimates would be particularly useful if one is only concerned with flood risk over a short future time horizon up to about one year, such as during the construction phase of a major infrastructure project.

The sequence in **Figure 1c** appears similar to **Figure 1b**, with the important difference that the frequency of the underlying climate mode is much lower, such that the historical record only contains one or two periods in either phase. The implications of this type of variability is that the record may represent a biased estimate of what will happen in the future, with our example showing two periods of above average flood risk and one period of below average flood risk. The implications can be seen by considering the probability density functions shown in the right panel, in which the underlying population distribution (black solid line) provides the best estimate for what will occur on average over an arbitrary future time horizon, while the distribution derived just by considering the last 100 data points (black dashed line) shows a significant overestimation of flood risk due to the bias induced by the small sample size.

Next, the sequence in **Figure 1d** concerns the case of a long-term trend component, which for the purposes of the example we assume to be linear. The source of such a trend might be due to climate oscillations at a frequency much lower than the period of record, or a gradual shift in climate such as might be attributed to anthropogenic climate change. Considering the right panel, the probability distribution indicated by the black solid line represents the variability over the full 100 year record, while the distribution indicated by the black dashed line represents the variability over the last half of the record, showing that flood estimation now becomes conditional to the period of record. Importantly, both estimates do not represent what will occur in the future, such that future flood risk can only be quantified based on some assumption as to the nature of the underlying trend.

Finally, the sequence in **Figure 1e** shows a step change in the second half of the record, in which the climate shifts from one ‘state’ to another. This arguably represents the most difficult form of non-stationarity to address, since the timing and magnitude of such shifts are usually impossible to predict. Nevertheless, the implications of anthropogenic climate change are that the likelihood of such shifts will increase in the future (Lenton *et al*, 2008). Once again the probability distribution represented by the solid black line (right panel) was derived using the full instrumental record, while the black dashed line was derived using only data after the step change; the appropriate distribution depends on what is assumed for the future, and in particular on whether the step change is expected to be a permanent or temporary feature of the local hydroclimate.

The obvious conclusion from this example is that the simple statement that the climate is non-stationary is not sufficient; one must understand the source(s) of non-stationarity if there is to be any chance of successfully representing future flood risk. In the next section we describe some of the sources of non-stationarity in the context of Australian flood risk.

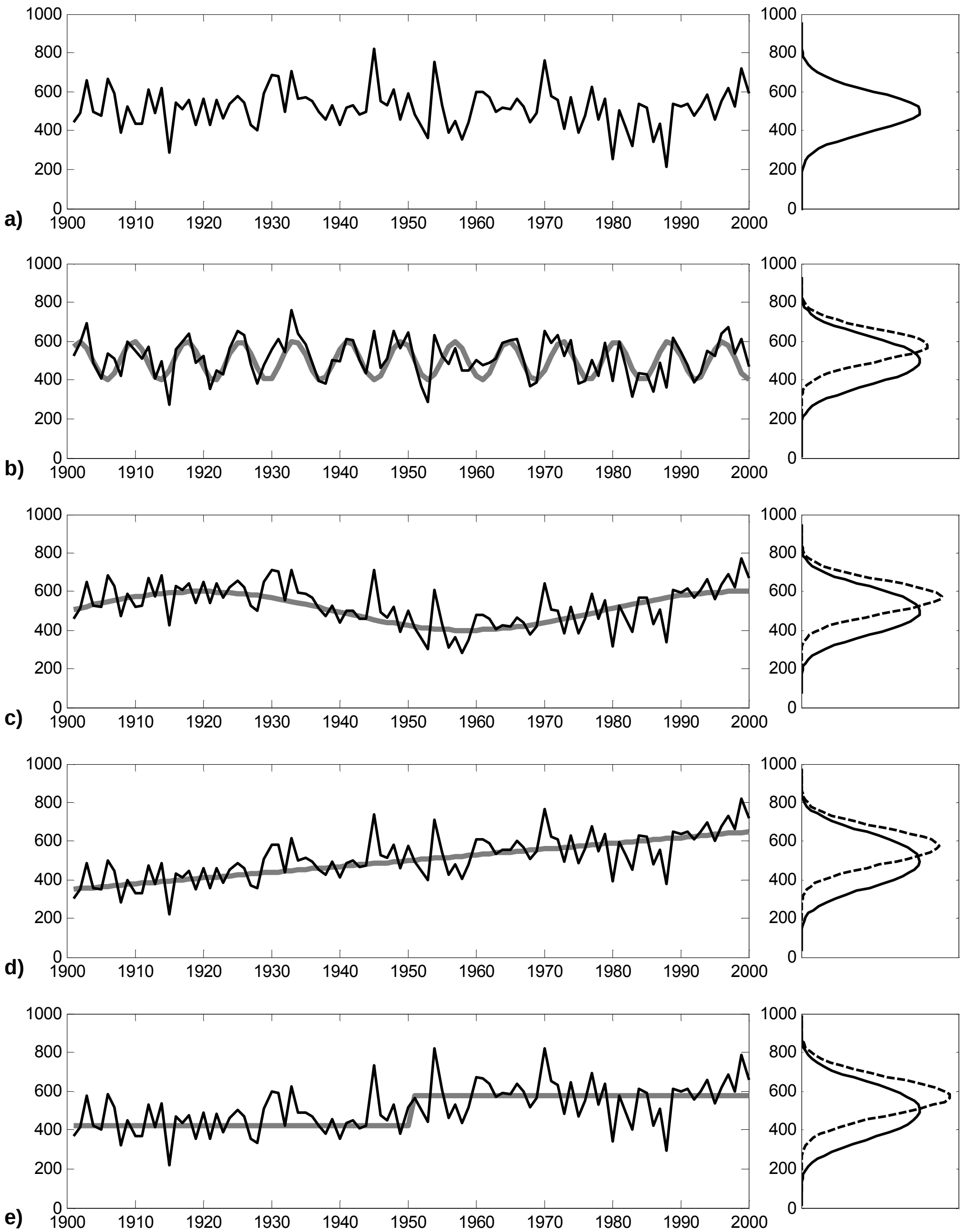

Figure 1: The implications of different forms of non-stationarity in evaluating future flood risk. The left panels represent a randomly generated sample of length 100, and the right panels represent the underlying population distribution, including the unconditional sample distribution (black solid line) and a conditional distribution based on only a subset of the data (black dashed line). Panel (a) comprises a normally distributed stationary time series, with the remaining panels being the summation of the data in (a) (thin black line) and an underlying non-stationarity component (thick gray line). Specifically: (b) represents cyclical variability with a period much shorter than the period of record; (c) represents cyclical variability with period of similar length to the period of record; (d) represents a long-term trend; and (e) represents a step change.

3. Climate variability and change in Australia

It should now be clear that different assumptions on the form of non-stationarity would lead to different conclusions about future flood risk. Using the idealised example presented in **Figure 1** as our starting point, we now ask: what are the dominant sources of climatic non-stationarity in Australian hydroclimatic data? And what approaches are available to estimate their future evolution?

3.1. 'Natural' modes of climate variability

It is now well understood that the climate varies naturally at scales ranging from sub-annual through to decadal and longer. Much of this variability is driven by low-frequency shifts in the atmosphere's lower boundary conditions (Goddard *et al*, 2001) as these evolve at time scales much longer than that for individual weather events. Relevant boundary conditions include global sea surface temperatures (SSTs), soil moisture, vegetation, snow and sea ice cover, with SSTs generally regarded as the dominant forcing variable for atmospheric circulation at the seasonal time scale (Goddard *et al*, 2001; Barnston *et al*, 2005). By influencing the water and energy balance in the atmosphere, variability in these lower boundary conditions can influence the probability of below- and above-average precipitation, including the likelihood of flood-producing precipitation events.

To simplify matters, these low-frequency variations are usually represented by climate indices, which are mathematically efficient representations of dominant modes of climate variability. These indices necessarily only partially represent all the relevant modes of precipitation variability (for example see Westra and Sharma, 2007, for a discussion on the limitations of using a single index of ENSO for capturing inter-annual and inter-decadal variability in annual average precipitation across Australia), but nevertheless provide a useful tool for identifying how climate influences flood risk. Climate modes and their respective indices which have been demonstrated to influence Australian precipitation include:

- the El Niño Southern Oscillation (ENSO) phenomenon, which is a coupled ocean-atmospheric mode centred on the tropical Pacific Ocean, varies at a time scale of 3 to 7 years and influences precipitation patterns across much of the world (Dai and Wigley, 2000). ENSO constitutes the best known, and arguably most influential, source of interannual precipitation variability in Australia, with the El Niño (La Niña) phase typically corresponding to drier (wetter) than average conditions across most of the continent.

- the Madden-Julian Oscillation (MJO; Madden and Julian, 1972; Zhang 2005), which oscillates with a frequency of 30-80 days and most strongly influences tropical northern Australian summer rainfall, but recently also has been found to have some influence over much of extra-tropical Australia (Wheeler *et al*, 2009).

- the Indian Ocean Dipole (IOD), which is a coupled ocean-atmosphere phenomenon characterised by anomalous cooling of SSTs in the south eastern equatorial Indian

Ocean and anomalous warming of SSTs in the western equatorial Indian Ocean (Saji *et al*, 1999; Webster *et al*, 1999), although the representation of the IOD as a physically distinct mode has been recently questioned (Dommenget and Jansen, 2009). Nevertheless, Indian Ocean variability has been found to have a statistically significant influence on western, southern and south-eastern Australian rainfall at the seasonal or monthly scale (e.g. Ashok *et al*, 2003; Ummenhofer *et al*, 2009), with the implications on climate extremes are less well known.

- the Southern Annular Mode (SAM), which represents a pressure dipole between the high- and mid-latitudes of the Southern Hemisphere. This constitutes the principal mode of variability of atmospheric circulation in the southern hemisphere extra-tropics (Trenberth *et al*, 2007), and explains about the same amount of variance of south-eastern Australia compared to that of ENSO. The positive phase is associated with below average rainfall in the southern regions of Australia and increases in the Murray-Darling Basin in summer (Hendon *et al*, 2007). A recent study also linked both the ENSO phenomenon and the SAM to increases in summer extreme rainfall in the northwest of the basin in summer, and decreases over the southwest in winter in the Swan-Avon River basin in Western Australia (Aryal *et al*, 2009).

- the Inter-decadal Pacific Oscillation (IPO; Power et al, 1999), which represents a multi-decadal sea surface temperature pattern centred in the Pacific Ocean. The degree to which the IPO and ENSO represent distinct physical phenomena has been subject to considerable debate (e.g. see discussion in Parker *et al* and references therein), with the IPO series being highly correlated to various indices of ENSO. Nevertheless, this mode has been shown to influence rainfall patterns in the tropics (Meinke et al, 2005), and flood risk in parts of eastern Australia (Kiem *et al*, 2003; Micevski *et al*, 2006), with a partial correlation analysis of Jain and Lall (2001) showing that the inter-decadal mode provides some additional climate information beyond ENSO.

Although each climate mode influences Australian rainfall variability and/or flooding, these modes are unlikely to impact on the stationarity assumption when estimating long-term flood risk unless: (1) the frequency of variability is approximately equal to or lower than the period of record, such that the instrumental record may be biased to one of the phases (corresponding to **Figure 1c**); or (2) the climate mode is observed or projected to change behaviour, possibly as a result of anthropogenic climate change, such that the past evolution of the mode is not an accurate reflection of how it will develop in the future (corresponding to **Figure 1d** or **1e**).

In the former case, the IPO is the climate mode that is most likely to impact upon future flood frequency estimates in Australia, as the period of oscillation is of a similar magnitude to a typical precipitation or flood record. The IPO index is reproduced in **Figure 2**, and shows that it has been in its positive phase approximately 65% of the time during the 20th century, including most of the period since 1977, with the positive phase corresponding to below-average flood frequency in parts of eastern Australia (Kiem *et al*, 2003). In consequence, using short flood records may result in an underestimation of future flood risk in regions where the IPO is found to be relevant, with an arguably better alternative being to use a historical sample which is unbiased to either IPO phase as a basis for developing the flood estimates.

Care needs to be taken when extrapolating these results to the future. In particular, due to the approximately instantaneous relationships between sea surface temperature variability and precipitation (see Westra and Sharma, 2009), although the IPO is usually represented as a highly smoothed series (**Figure 2**, thick gray line), the precipitation variability is more likely to follow the variability represented by the unsmoothed series (thin black line). This means that, although the IPO tends to vary at a low frequency, the transition from a positive to a negative phase provides little indication that it will remain in that same phase for any prescribed period time, making long-term prediction difficult (see also Power *et al*, 2006). In addition, there is considerable debate about the spatial coherence of the IPO over the extended paleo-climatological record prior to the 20th century (for example refer to the discussion in Gedalof *et al*, 2002; Linsley *et al*, 2004; D'Arrigo *et al*, 2005; Verdon and Franks, 2006; Linsley *et al*, 2008), such that the long-term relationship between inter-decadal variability in the Pacific Ocean and Australian rainfall variability is the subject of ongoing research. Finally, as will be discussed later, climate models have difficulty in accurately simulating variability at the interdecadal timescale (Lin, 2007), making inference about the future evolution of this mode as a result of anthropogenic climate change difficult. For these reasons we suggest that, at present, the principal value of the IPO index in applied flood hydrology is to emphasise the need to use a precipitation record which is not biased to a single IPO phase, with this being most easily achieved through use of long instrumental records as the basis of the analysis.

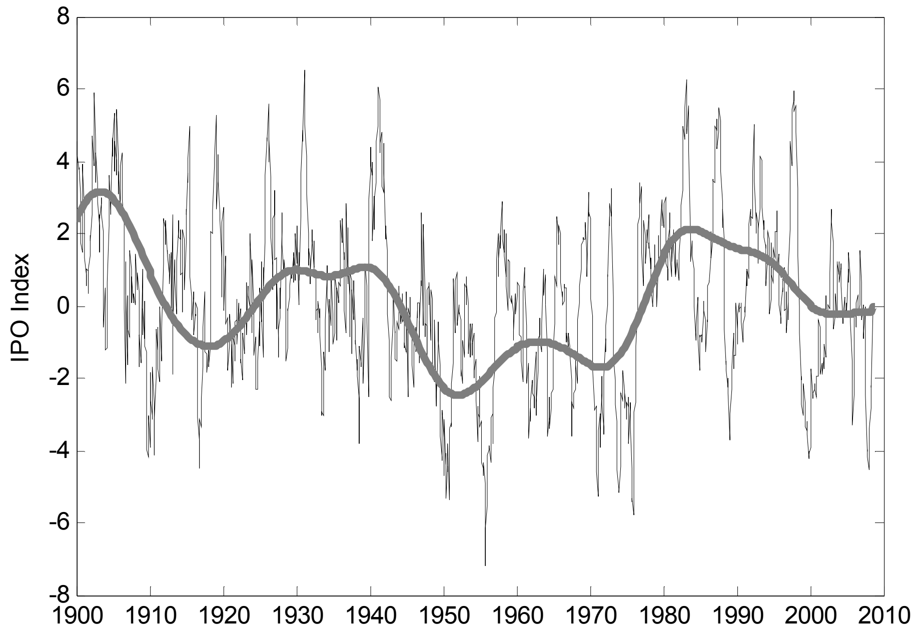

Figure 2: The Inter-decadal Pacific Oscillation (IPO) index from 1900 to the present obtained from www.iges.org/c20c/IPO_v2.doc. Two versions are shown: the smoothed version (thick gray line) derived after smoothing on time scales greater than 11 years, showing multi-decadal periods in which the index is either positive or negative; and the raw series (thin black line) which similarly shows dramatic step changes in 1945 and 1977, but which nevertheless highlights the difficulty in developing projections as to how this index will evolve in the future based on extrapolations alone. The correlation coefficient between the unsmoothed IPO series and the Niño 3.4 representation of ENSO over the period from 1871 to 2008 is 0.83, highlighting that these modes are closely related.

The issue of possible shifts in the dynamics of key climate modes as a result of anthropogenic climate change is much more difficult to address, but potentially of much greater consequence. For example, recently the SAM has spent more time in its positive phase, potentially contributing to the observed decline in precipitation in much of Australia's south (CSIRO, 2007; Aryal *et al*, 2009; Nicholls, 2009). The attribution of this trend remains unclear, however, and variously has been related to stratospheric ozone depletion, anthropogenic climate change or low-frequency variability resulting from natural forcing (Trenberth *et al*, 2007), with an extended reconstruction of the SAM suggesting that the recent warming may not be unusual over the historical record (Visbeck, 2009). In contrast, a recent reconstruction of ENSO events dating back to A.D. 1525 based on proxy records from a variety of sources (including tree-ring, coral, ice-cores and documentary evidence) concludes that although extreme ENSO events occurred throughout the 478 year reconstruction, 43% of the extreme and 28% of the protracted events occur in the 20th century, suggesting that ENSO may be strengthening due to anthropogenic climate change (Gergis and Fowler, 2009; see also Conroy *et al*, 2009). Similarly, a reconstruction of the IOD back to 1846 suggests an increase in the frequency and strength of IOD events during the 20th century (Abram et al, 2008).

Thus we may be beginning to see observational evidence that several important modes of climate variability are changing behaviour as a result of anthropogenic climate change, with associated implications on stationarity. It is therefore reasonable to ask: what evidence is there of changes in the nature of extreme precipitation in the Australian instrumental record? And what can be said about how extreme precipitation may vary in the future?

3.2. Anthropogenic climate change

The discussion thus far has focused on a range of 'natural' modes of climate variability, and the associated implications for flood estimation. It was suggested that, in the absence of trends and step changes that might be attributable to anthropogenic climate change, the non-stationarity in these modes is relatively easy to handle provided one has available a historical dataset which is representative of the full envelope of variability represented by each of these modes. The most significant challenge concerns variability at decadal and longer time-scales, which can result in biased estimates of future flood risk (Jain and Lall, 2001).

Unfortunately, the validity of the historical record (including both the instrumental and paleo-climate record) becomes increasingly questionable in directly evaluating flood risk in the light of anthropogenic climate change. In particular, the recent atmospheric concentration of carbon dioxide of about 380 ppm has exceeded the natural range of greenhouse forcing over at least the last 650,000 years (ranging from about 180 to 300 ppm; CSIRO, 2007), with further increases expected over the coming decades, such that the instrumental record does not capture the impacts of such enhanced greenhouse gas forcing.

From a precipitation perspective, implications for flood risk are present both in possible changes to the likelihood of extreme flood-producing precipitation events, and in the seasonal or annual average precipitation which will influence antecedent moisture conditions and hence the conversion of rainfall to runoff, with the relative importance dependent on the hydrologic properties of the catchment being analysed (Hill *et al*., 1997). To determine the likely characteristics of future precipitation, we first evaluate the degree to which trends in the instrumental record can be observed in both the means and extremes of precipitation, and next describe some recent general circulation model (GCM)-derived projections.

3.2.1 International trends

While there have been numerous analyses of precipitation trends in the international literature, there are relatively few papers that focus on changes in precipitation extremes. Nevertheless, increases in the intensity of rainfall over extensive regions have been found by several authors. For example Pielke and Downton (2000) analysed data from the contiguous United States over the period 1932 to 1997, and found significant increases in the number of wet days and two-day precipitation extremes. In Europe, Klein Tank and Konnen (2003) found evidence for increasing trend in six out of seven precipitation extremes averaged across Europe ; Schmidli and Frei (2005) report a clear increasing trend in intensity of winter and autumn heavy precipitation in Switzerland, and Brunetti *et al* (2004) found an increase in precipitation intensity in Italy. Despite a trend for decreasing total rainfall in Italy and Spain, Alpert *et al* (2002) found that extreme rainfalls have increased. In India, Roy and Balling (2004) found an increase in the frequency of large precipitation events over the period 1910 to 2000.

3.2.2 Australian precipitation trends

Recently a large number of studies have been conducted to analyse trends in Australian rainfall (see Gallant *et al*, 2007, for a summary of studies on changes in Australian rainfall conducted since 1992). Robust statistical results are best obtained by examining annual and seasonal rainfall, as well as ‘extremes’ which occur relatively frequently over the instrumental record, such as the 95^{th} and 99^{th} percentile daily rainfall event. Due to the comparatively high density of rain gauges measuring daily rainfall, the research emphasis also has been on trends in daily or longer timescales, rather than the sub-daily storm bursts which are particularly relevant for small urban catchments (Beecham and Chowdhury, 2009). Thus, there is limited information on flood-producing extreme precipitation events which occur with low exceedance probabilities (e.g. the 1 in 100 AEP event) and which are often at the sub-daily timescale.

The most striking trend in the historical Australian precipitation record has been a decline in average annual rainfall in southwest Western Australia, with declines in south eastern Australia and the eastern coastal region also evident although with less statistical significance (Gallant *et al*, 2007; Alexander *et al*, 2007; CSIRO 2007). Changes in extreme rainfall in these regions have been found to be of generally the same sign as annual or seasonal averages (CSIRO, 2007), although Groisman *et al* (2005) show an increasing trend in the number of days with precipitation greater than the 99.7 percentile in south eastern Australia (see also Gallant *et al*, 2007, who find that the proportion of total annual/seasonal rainfall coming from events above the seasonal 95th percentile has increased significantly in this region since 1910). The northwest of Australia shows a positive trend in average summer rainfall since 1950 (CSIRO 2007), although the absence of high quality daily precipitation data in this region makes detection of trends in extreme rainfall difficult (Alexander *et al*, 2007).

In describing these trends, it is important to note that much of the observed precipitation variability may be due to natural climate variability at inter-annual and inter-decadal time scales (e.g. Lambert *et al*, 2005), with the direction of the trend often being conditional to the time period of analysis (for example refer to the discussion in Gallant *et al* (2007) on observed trends in south eastern Australia). The limited historical record and strong influence of natural climate variability makes the detection of historical trends and attribution to anthropogenic climate change difficult (e.g. see discussion in Giorgi and Bi, 2009; Alexander and Arblaster, 2009), with associated implications for extrapolating observed trends into the future.

3.2.3 Climate change projections

The above discussion highlights the difficulties in using the historical record for estimating what will occur in the future. As will be discussed in the sections that follow, projections for extreme precipitation under an anthropogenically warmed climate based on climate model simulations are generally for an increase across much of Australia (CSIRO, 2007), even for areas with projected decreases in average annual precipitation. The physical reasoning for this is that high-intensity short-duration events are more directly influenced by the water-holding capacity of the atmosphere as governed by the Clausius-Clapeyron equation, rather than on the total energy budget of the atmosphere which constrains mean global precipitation increases (e.g. Frei *et al*, 1998; Trenberth *et al*, 2003; Meehl et al, 2007; Bates *et al*, 2008; Lenderink and van Meijgaard, 2008; Allan and Soden, 2008; Bengtsson *et al*, 2009). In fact, the rate of increase in extremes can theoretically even exceed the Clausius-Clapeyron scaling of about 7% per degree change in atmospheric temperature because the additional latent heat released in convective storms can feed back and further invigorate the storm (Rasmussen *et al*, 2008), with a recent study suggesting approximately double the Clausius-Clapeyron scaling for 1-hour precipitation extremes in Europe based on both observations and modelled output (Lenderink and van Meijgaard, 2008).

An alternative to directly applying the historical record to estimating future precipitation changes involves the use of general circulation models (GCMs) to simulate how climate will respond to increased greenhouse gas forcing in the future. These GCMs encompass a broad class of numerical models that represent various components of the climate system including the atmosphere, oceans, land surface and sea-ice (CSIRO, 2007). The most complex GCMs are known as coupled Atmospheric-Oceanic General Circulation Models (AOGCMs), with a total of 23 AOGCMs used to support the most recent Intergovernmental Panel on Climate Change (2007) projections. How reliable are these models? And to what extent can they be applied directly to estimate changes to future flood risk?

The IPCC, in their fourth assessment report, have found climate models to provide ‘credible quantitative estimates’ of future climate change, with models being unanimous in their prediction of substantial climate warming resulting from greenhouse gas increases, and with projections being consistent with independent estimates derived from other sources, such as from observed climate changes and past climate reconstructions (Randall *et al*, 2007). Despite this, the current generation of GCMs have significant limitations in providing projections necessary for flood estimation, in part because:

- Projections are generally significantly more robust at the continental and global scale, compared to the regional and catchment scales;

- Inter-annual and inter-decadal variability due to the ENSO phenomenon and other climate modes are often not accurately captured in climate model simulations (e.g. AchutaRao and Sperber, 2006; Lin, 2007), and the extent to which GCMs represent key climate feedback processes is not fully determined;

- The intensity, frequency and distribution of extreme precipitation is generally not well simulated, as current climate models do not realistically represent many of the processes important to the formation of clouds and precipitation at the relevant temporal and spatial scales (Rasmussen *et al*, 2008).

To illustrate these issues, a recent study on GCM consistency by Johnson and Sharma (2009) compared the outputs of nine GCMs for eight different variables and two emissions scenarios, using a specially developed Variable Convergence Score which evaluates the level of agreement between GCMs across Australia. The results, presented in **Table 1**, show that variables such as surface pressure and temperature have comparatively high levels of consistency, while precipitation, usually the most important variable from a flood risk perspective, scores the lowest.

Table 6: GCM variable 'skill score' (expressed as a %) for a 20-year window centred at 2030 for two SRES emission scenarios (IPCC, 2000). These scenarios represent plausible future greenhouse gas emission trajectories, with the A2 scenario representing a future with high population growth, slow economic growth and slow technological change, while B1 represents a future with population growth peaking in mid-century and a rapid transition to a service and information economy. A skill score of 100% denotes consistency in future simulations across the GCMs (Johnson and Sharma, 2009).

VARIABLE	SRESA2	SRESB1
Temperature	72	82
Wind Speed	42	50
Longwave Radiation	24	24
Shortwave Radiation	68	69
Specific Humidity	53	51
Precipitation	***7***	***7***
Precipitable Water	53	53
Surface Pressure	97	99

To overcome the limitations of GCMs in modelling the fine-scale processes relevant for evaluating the implications of climate change on extreme precipitation, it is necessary to downscale GCM results (Fowler *et al*, 2007). Downscaling approaches may be classified as either dynamical, where a higher-resolution regional climate model is embedded within a GCM, or statistical, for which empirical relationships are developed between climate fields derived from GCMs and the local climate variable of interest. Comparison studies of different downscaling approaches generally do not provide substantive evidence in favour of either dynamical or statistical approaches, with the absence of a consistently superior downscaling method indicating the need for a range of statistical and dynamical methods to be applied for climate impact assessments, with convergence between several of the independent approaches adding confidence to the projections (see Fowler *et al*, 2007 for a detailed review). The inconsistent performance of downscaling approaches also highlights the need for the performance of the models over the 20th century to be explicitly described as part of any downscaling study, preferably on a validation dataset which was not used in training the downscaling model, so that decision makers can make inferences about the trustworthiness of the outputs in representing future change. In Australia, such analyses are urgently needed to better understand the certainty that can be ascribed to any downscaling projections.

Although no Australia-wide projections of precipitation extremes are currently available, there have been numerous regional studies published which provide an indication of how extreme precipitation might change in the future. These studies largely have been derived using a regional climate modelling approach at the daily timescale, and typically find that the return period of extreme rainfall events will halve in the late 21st century simulations compared to the historical record (Christensen *et al*, 2007). Recently, several studies which explicitly model sub-daily precipitation processes using CSIRO's Regional Atmospheric Modelling System (RAMS), a high-resolution modelling system developed for the simulation of extreme rainfall events, show increases of 2-hr extreme precipitation of more than 70% for both 2030 and 2070 for southeast Queensland (Abbs *et al*, 2007), and of 10-20% by 2030 and potentially more than 60% by 2070 for the Western Port region of Victoria (Abbs and Rafter, 2008). These results should be treated with caution, however, and significant additional work is required to develop improved uncertainty estimates, as well as reconciling observed trends in the historical record with projections of future changes. Nevertheless, such projections of a disproportionate increase in precipitation extremes for sub-daily rainfall would pose a significant challenge for urban systems, which typically have times of concentration much shorter than the daily timescale (Beecham and Chowdhury, 2009).

Finally, in contrast to precipitation extremes, seasonally and annually averaged precipitation over much of Australia is projected to decrease (CSIRO, 2007), indicating that a greater proportion of the annual precipitation will be concentrated in a relatively small number of short-duration storm-bursts with a corresponding decrease in moderate precipitation days and increase in the number of dry days. The effects of antecedent moisture conditions therefore may become increasingly relevant in flood estimation in a changed climate, as this may partially offset the impacts of increased storm-burst intensity, particularly for catchments with high infiltration rates and/or large storage volumes. Continuous rainfall simulation, in which extended synthetic sequences are generated to preserve certain characteristics of the historic rainfall record, is likely to represent one of the principal tools to achieve this, and the development of approaches to account for anthropogenic climate change in these continuous rainfall sequences represents an important area of continuing research.

4. Implications on flood estimation practice

Increasingly, the hydrological community needs to be cognisant of the implications of climate variability and change on hydroclimatic data relevant for the estimation of flood risk. This paper has sought to provide a brief overview of some of the key issues, including an appraisal of recent research on the sources of non-stationarity and a discussion of approaches for estimating future changes to flood frequency resulting from anthropogenic climate change.

Based on our current understanding of climate variability and change, a prescriptive outline of how to address non-stationarity is not currently possible. Nevertheless, it is possible to provide the following general conclusions:

1. Based on the analysis of instrumental and proxy records, it is apparent that the climate varies at a range of temporal scales, such that the use of short precipitation or flood records are unlikely to properly capture the envelope of climate variability. Although the ideal record length for flood estimation is highly subjective, it was recently demonstrated that a record length of 30 years would result in significant misspecification of flood risk (Jain and Lall, 2001; see also Thyer et al, 2006). It is worth noting that climate shifts tend to occur over large spatial scales, so that in cases where long records are not available in the catchment of interest, extended records in neighbouring regions might be useful to inform the estimation process (see Salas, 1993 for a discussion of available methods for record extension).

2. The practice which we will term ‘non-stationarity diagnostics’, i.e. the analysis of instrumental data for cycles, trends and/or step changes, will become of increasing importance in the assessment of flood risk for large and/or significant projects.

3. There is currently no consistent Australia-wide information on the implications of anthropogenic climate change on flood risk. It is still not clear what advice will be provided in the revised Australian Rainfall and Runoff guidelines in this regard, as this depends on the outcomes of future climate modelling studies. Nevertheless, it is recognised that for simple applications climate ‘factors’, possibly expressed as a percentage increase in precipitation intensity compared to Intensity-Frequency-Duration relationships derived from the instrumental record, may be necessary. The extent to which such estimates can be generalised across space, recurrence interval, storm-burst duration, and future time horizon still require determination.

4. For cases where the consequences of incorrectly specifying future flood risk are serious (such as in the design of large flood protection works), a more detailed site-specific downscaling study may be useful to consider. Although downscaling approaches for estimating the probability of extreme hydrological events are still in their infancy, the advantage of these tools is that by comparing the performance of the downscaling model to historical data, the accuracy of future projections can be

explicitly described and thus accounted for when making decisions about future change.

5. The estimation approach, and in particular the extent to which we account for anthropogenic climate change, must become conditional to a future time horizon. If, for example, one is concerned with flood risk only over the next few years, and no significant trend in flood risk has been observed over the historical record, then the implications of future climate change may be minor compared to the envelope of natural climate variability such that traditional flood estimation methods might still be applicable. In contrast, if one is concerned with the flood risk several decades or more into the future, then one must consider anthropogenic climate change explicitly.

6. To account for the uncertainty inherent in the estimation of climate change and its impacts, it may be beneficial to develop a staged, adaptive approach to design. To this end we must provide an assessment of flood risk based on current conditions, as well as for conditions that will be applicable over the design life of the flood mitigation works. Depending on the nature of the works being considered, it may be cost effective for the works to be implemented in a staged fashion where the need for each successive step is evaluated on a regular basis. The implications of progressively increasing the degree of flood protection over time will need to be accommodated in the initial design, and the benefits of the staging will need to be explicitly balanced against the changing estimates of the annualised risk costs involved.

7. Finally, practicing hydrologists increasingly will be called on to assess the implications of climate variability and change on the probability of extreme events, as well as appraising the strength and weaknesses of various estimation techniques. It therefore will be necessary for the applied and research communities to work together to ensure rapid dissemination of scientific developments as they occur.

Having made the above points, it is necessary to ensure that any guidelines that are developed, take into account the significant uncertainty there exists in climate model simulations of the future (as illustrated by Johnson and Sharma, 2007, and Table 1 of this paper). If climate change “factors” are the way to provide recommendations for the future, they must be based on multiple climate model simulations instead of a single one. If “stationary” design estimates are desired representative of a fixed time window, climate model simulations corresponding to a fixed CO_2 concentration (the so called stabilisation scenarios) should be employed. Needless to say, all of this is prohibitive from a computational point of view, pointing to the need for developing simulation options that are efficient and still acceptably accurate. There is a need for significant additional research in this area.

To summarise, apart from a reaffirmation of the importance of long, accurate historical records, the optimum approach for flood estimation in our non-stationarity world will depend, *inter alia*, on the size of the problem, the consequences of incorrectly specifying flood risk, and the future time horizon. Guidelines such as the forthcoming Australian Rainfall and Runoff will increasingly be called on to provide specific guidance. Nevertheless, as many of the themes described in this paper are the focus of an ongoing research effort, significant developments in our understanding will continue to occur in the coming years.

5. Conclusions

The assumption of stationarity effectively imposes the constraint that what will occur in the future must mirror what has occurred in the past. The significant sources of uncertainty associated with non-stationarity as described in this paper, and thus the difficulty in providing specific advice on estimating future flood risk, comes necessarily from the rejection of this constraint; in effect, if the future does not reflect the past, then we must consider a much wider range of possibilities. Or, written differently, as a result of non-stationarity 'we must expect to be surprised more than we expect' (Jain and Lall, 2001).

Importantly, in many cases even specifying the uncertainty bounds becomes difficult. For example we do not know what the future trajectory of greenhouse gas emissions will be; similarly, although the likelihood of dramatic climate shifts becomes increasingly high as the climate warms, the nature and timing of such shifts are generally unknown (e.g. Lenton *et al*, 2008). Thus even the probability density function surrounding an estimate will contain significant subjectivity.

We therefore conclude by suggesting that good design practice should henceforth include the need to address *the non-stationary character* of flood risk. To this end, the design process should include the need for a sensitivity analysis by simulating a range of plausible future climate scenarios and evaluating the consequences should any such scenario eventuate. This concept becomes increasingly relevant for cases where the consequences of incorrectly specifying future climate is deemed to be significant, and as such might form the basis of the design and operation of large infrastructure or the evaluation of the implications of planning decisions such as zoning for development. To accommodate this inherent uncertainty, it may be prudent to adopt a staged, adaptive approach to design, whereby solutions are implemented in a staged fashion and the need for each successive step is evaluated periodically.

To inform such a sensitivity analysis, the specification of uncertainty might be expressed as a full probability density function based on a detailed downscaling study at the location of interest, or only be provided in qualitative terms – for example a particular outcome is 'likely' or 'highly unlikely' to occur – but this will nonetheless inform any decision based on risk and consequence. This conceptual approach provides an advantage over the assumption of stationary flood risk in that it allows the decision maker to consider a much broader range of possibilities, and weigh them against a range of non-scientific factors such as engineering (what are the technical alternatives? can the design accommodate staged construction?), economic (what is the present cost of action compared to the future cost of inaction? are there benefits to progressive implementation?) and political (what level of risk is 'acceptable'?) considerations.

The concepts of sensitivity testing and adaptive design emphasises the need to consider many issues surrounding climate uncertainty and adaptation to climate change. The best the flood practitioner can do to inform this process is to remain aware of developments in climate science, explain the range of possible outcomes resulting from different assumptions on how the climate will evolve, and accurately convey the relative confidence that should be held in any of their assessments and projections.

References

Abbs, D., 2007, The impact of climate change on extreme rainfall and coastal sea levels over south-east Queensland - Part 2: A high-resolution modelling study of the effect of climate change on the intensity of extreme rainfall events, consultancy report prepared for the Gold Coast City Council, CSIRO, 39pp.

Abbs, D. & Rafter, T., 2008, The effect of climate change on extreme rainfall events in the Western Port Region, CSIRO Marine and Atmospheric Research (available at http://www.wpga.org.au/ppp.asp).

Abram, N.J., Gagan, M.K., Cole, J.E., Hantoro, W.S. & Mudelsee, M., 2008, Recent intensification of tropical climate variability in the Indian Ocean, *Nature Geoscience*, 1, 849-853.

AchutaRao, K. & Sperber, K.R., 2006, ENSO simulation in coupled ocean-atmosphere models: are the current models better? *Climate Dynamics* 27: 1-15, doi: 10.1007/s00382-006-0119-7.

Alexander, L.V., Hope, P., Collins, D., Trewin, B., Lynch, A. & Nicholls, N., 2007, Trends in Australia's climate means and extremes: a global context, *Australian Meteorological Magazine*, 56, 1-18.

Alexander, L.V. & Arblaster, J.M., 2009, Assessing trends in observed and modelled climate extremes over Australia in relation to future projections, *International Journal of Climatology*, 29, 417-435.

Alpert P, Ben-Gai T, Baharad A. 2002. The paradoxical increase of Mediterranean extreme daily rainfall in spite of decrease in total values. *Geophysical Research Letters* **29**: 1536.

Allan, R.P. & Soden, B.J., 2008, Atmospheric warming and the amplification of precipitation extremes, *Science*, 321, 1481-1484.

Aryal, S.K., Bates, B.C., Campbell, E.P., Li, Y., Palmer, M.J. & Viney, N.R., 2009, Characterizing and Modeling Temporal and Spatial Trends in Rainfall Extremes, *Journal of Hydrometeorology*, Vol. 10, doi: 10.1175/2008JHM1007.1

Ashok, K., Guan, Z. & Yamagata, T., 2003, Influence of the Indian Ocean dipole on the Australian winter rainfall, *Geophysical Research Letters*, 30(15), 1821, doi: 10.1029/2003GL017926.

Barnston, A.G., Kumar, A., Goddard, L. & Hoerling, M.P., 2005, Improving seasonal prediction practices through attribution of climate variability, *Bulletin of the American Meteorological Society*, 86 (1), 59-72.

Bates, B.C., Kundzewicz, Z.W., Wu, S. & Palutikof, J.P., (Eds), 2008, Climate Change and Water. Technical Paper of the International Panel on Climate Change, IPCC Secretariat, Geneva, 210 pp.

Beecham, S. & Chowdhury, R.K., 2009, Temporal characteristics and variability of point rainfall: a statistical and wavelet analysis, *International Journal of Climatology,* DOI: 10.1002/joc1901.

Bengtsson, L., Hodges, K.I. & Keenlyside, N., 2009, 2009, Will extratropical storms intensity in a warmer climate? *Journal of Climate*, Vol 22, doi: 10.1175/2008JCLI2678.1.

Brunetti, M., L. Bufoni, F. Mangianti, M. Maugeri, T. Nanni. 2004. Temperature, precipitation and extreme events during the last century in Italy. *Global Planet Change* 40: 141-149.

Christensen, J.H., B. Hewitson, A. Busuioc, A. Chen, X. Gao, I. Held, R. Jones, R.K. Kolli, W.-T. Kwon, R. Laprise, V. Magaña Rueda, L. Mearns, C.G. Menéndez, J. Räisänen, A. Rinke, A. Sarr and P. Whetton, 2007: Regional Climate Projections. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Conroy, J.L., Restrepo, A., Overpeck, J.T., Steinitz-Kannan, M., Cole, J.E., Bush, M.B. & Colinvaux, P.A., 2009, Unprecedented recent warming of surface temperatures in the eastern tropical Pacific Ocean, *Nature Geoscience*, Vol. 2, doi: 10.1038/NGEO390.

CSIRO, 2007, Climate Change in Australia, Technical Report 2007 (available from www.climatechangeinaustralia.com.au)

D'Arrigo, R., Wilson, R., Deser, C., Wiles, G., Cook, E., Villalba, R., Tudhope, A., Cole, J. & Linsley, B., 2005, Tropical-North Pacific Climate Linkages over the Past Four Centuries, *Journal of Climate*, 18, 5253-5265.

Dai, A. & Wigley, T.M.L., 2000, Global patterns of ENSO-induced precipitation, *Geophysical Research Letters*, 27: 1283-1286.

Dommenget, D. & Jansen, M., 2009, Prediction of Indian Ocean SST indices with a simple statistical model: a null hypothesis, *Journal of Climate* (accepted manuscript – 14/04/2009).

Frei et al, 1998: Heavy precipitation processes in a warmer climate. *Geophysical Research Letters*, 25(9): 1431-1434.

Gallant, A.J.E., Hennesy, K.J. & Risbey, J., 2007, Trends in rainfall indices for six Australian regions: 1910-2005, *Australian Meteorological Magazine*, 56, 223-239.

Gedalof, Z., Mantua, N. & Peterson, D., 2002, A multi-century perspective of variability in the Pacific Decadal Oscillation: new insights from tree rings and coral, *Geophysical Research Letters,* vol. 29 (24), doi: 10.1029/2002GL015824.

Gergis, J.L. & Fowler, A.M., 2009, A history of ENSO events since A.D. 1525: implications for future climate change, *Climatic Change*, 92: 343-387.

Giorgi, F. & Bi, X., 2009, “Time of emergence (TOE) of GHG-forced precipitation change hot-spots, *Geophysical Research Letters*, Vol. 36, L06709, doi: 10.1029/2009GL037593

Goddard, L., Mason, S.J., Zebiak, S.E., Ropelewski, C.F., Basher, R. & Cane, M.A., 2001, Current approaches to seasonal-to-interannual climate predictions, *International Journal of Climatology*, 21: 1111-1152.

Groisman, P.Y., Knight, R.W., Easterling, D.R., Karl, T.R., Hegerl, G.C. & Razuvaev, V.N., 2005, Trends in Intense Precipitation in the Climate Record, *Journal of Climate*, 18, 1326-1350

Hendon, H.H., Thompson, D.W.J. & Wheeler, M.C., 2007, Australian rainfall and surface temperature variations associated with the Southern Hemisphere Southern Annular Mode, *Journal of Climate*, 20, 2452-2467.

Hill, P.I., Mein, R.G., Weinmann, P.E., 1997 Development and Testing of New Design Losses for South-Eastern Australia*. 24th Hydrology and Water Resources Symposium Auckland 1997.*

I.E.Aust., (1997). "Australian Rainfall and Runoff". Published by the Institute of Engineers Australia, editor in chief, DH Pilgrim, 2 Vols.

Intergovernmental Panel on Climate Change (IPCC), 2007. *Climate Change 2007: Synthesis Report*. An Assessment of the Intergovernmental Panel on Climate Change. IPCC Plenary XXVII Valencia, Spain, 12-17 November 2007.

Intergovernmental Panel on Climate Change (IPCC), 2000, *Special Report on Emission Scenarios- Summary for Policy Makers,* A report of the IPCC Working Group III.

Jain, S. & Lall, U., 2001, Floods in a changing climate: Does the past represent the future?, *Water Resources Research*, 37 (12), 3193-3205.

Johnson, F. & Sharma, A., 2009, Measurement of GCM skill in predicting variables relevant for hydroclimatological assessments, *Journal of Climate*, in press, doi:

10.1175/2009JCLI2681.1

Kiem, A.S., Franks, S.W. & Kuczera, G., 2003, Multi-decadal variability of flood risk, Geophysical Research Letters, 30(2), 1035, doi:10.1029/2002GL015992.

Klein Tank A.M.G. and Konnen, G.P. 2003. Trends in indices of daily temperature and precipitation extremes in Europe, 1946-99. *Journal of Climate*, 16, 3665-3680.

Lambert, F.H., Gillett, N.P., Stone, D.A. & Huntingford, C., 2005, Attribution studies of observed land precipitation changes with nine coupled models, *Geophysical Research Letters* 32: L18704, 852-863.

Lenderink, G. & van Meijgaard, E., 2008, Increase in hourly precipitation extremes beyond expectations from temperature changes, *Nature Geoscience,* Vol. 1, doi: 10.1038/ngeo262.

Lenton, T.M., Held, H., Kreigler, E., Hall, J.W., Lucht, W., Rahmstorf, S. & Schellnhuber, H.J., 2008, Tipping elements in the Earth's climate system, *Proceedings of the National Academy of Sciences of the United States of America*, doi: 10.1073/pnas.0705414105.

Lin, J.L., 2007, Interdecadal variability of ENSO in 21 IPCC AR4 coupled GCMs, *Geophysical Research Letters*, Vol. 34, doi: 10.1029/2006GL028937.

Linsley, B.K., Wellington, G.M., Schrag, D.P., Ren, L., Salinger, M.J. & Tudhope, A.W., 2004, Geochemical evidence from corals for changes in the amplitude and spatial pattern of the South Pacific interdecadal climate variability over the last 300 years, *Climate Dynamics*, 22: 1-11. doi: 10.1007/s00382-003-0364-y.

Linsley, B.K., Zhang, P., Kaplan, A., Howe, S.S. & Wellington, G.M., 2008, Interdecadal-decadal climate variability from multicoral oxygen isotope records in the South Pacific Convergence Zone region since 1650 A.D., *Paleoceanography*, Vol. 23, doi: 10.1029/2007PA001539.

Madden, R.A. & Julian, P.R., 1972, Description of global-scale circulation cells in the tropics with a 40-50 day period. *Journal of Atmospheric Science*, 29, 1109-1123.

Meehl, G.A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, I.G. Watterson, A.J. Weaver and Z.-C. Zhao, 2007: Global Climate Projections. In: *Climate Change 2007: The Physical Science Basis.Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Meinke, H., DeVoil, P., Hammer, G.L., Power, S., Allan, R., Stone, R.C., Folland, C. &

Potgieter, A., 2005, Rainfall variability at decadal and longer time scales: signal or noise? *Journal of Climate,* 18, 89-96.

Micevski, T., Franks, S.W. & Kuczera, G., 2006, Multidecadal variability in coastal eastern Australian flood data, *Journal of Hydrology*, 327, 219-225.

Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P. & Stouffer, R.J., 2008, Stationarity is dead: Whither Water Management? *Science*, Vol. 319, pp 573-574.

Nicholls, N., 2009, Local and remote causes of the southern Australian autumn-winter rainfall decline, 1958-2007, *Climate Dynamics*, doi: 10.1007/s00382-009-0527-6.

Parker, D., Folland, C., Scaife, A., Knight, J., Colman, A., Baines, P & Dong, B., 2007, Decadal to multidecadal variability and the climate change background, *Journal of Geophysical Research,* Vol. 112, D18115, doi: 10.1029/2007JD008411.

Pielke, R.A. and Downton, M.W. 2000. Precipitation and damaging floods: trends in the United States, 1932-97*. Journal of Climate*, 13, 3625-3637.

Power, S., Haylock, M., Colman, R. & Wang, X., 2006, The predictability of interdecadal changes in ENSO activity and ENSO teleconnections, *Journal of Climate,* 19: 4755-4771.

Rasmussen, R., Aiguo, D. & Trenberth, K.E., 2008, *Impacts of Climate Change on Precipitation*, in Gad-el-Hak, M., (ed), Large-scale Disasters – Prediction, Control and Mitigation.

Randall, D.A., R.A. Wood., S. Bony, R. Colman, T. Fichefet, J. Fyfe, V. Kattsov, A. Pitman, J. Shukla, J. Srinivasan, R.J. Stouffer, A. Sumiand, K.E. Taylor, 2007, Climate models and their evaluation. In: *Climate Change, 2007: The Physical Science Basis.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Roy, S.S. and Balling, R.C. 2004. Trends in extreme daily precipitation indices in India, *International Journal of Climatology*, 24: 457-466.

Salas, J.D., 1993, *Analysis and Modelling of Hydrologic Time Series,* in Handbook of Hydrology, Maidment, D.E. (editor), McGraw-Hill, New York.

Saji, N.H., Goswami, B.N., Vinayachandran, P.N. & Yamagata, Y., A dipole mode in the tropical Indian Ocean, *Nature*, 401, 360-363.

Schmidli, J., C.H. Frei. 2005. Trends of heavy precipitation and wet and dry spells in Switzerland during the 20th Century. *International Journal of Climatology,* 25:753-771.

Thyer, M., Frost, A.J. & Kuczera, G., 2006, Parameter estimation and model identification for stochastic models of annual hydrologic data: Is the observed record long enough? *Journal of Hydrology*, 330 (1-2), 313-328.

Trenberth, K.E., Dai, A., Rasmussen, R. & Parsons, D., 2003, “The changing character of precipitation”, *Bulletin of the American Meteorological Society*, 84, 1205-1217.

Trenberth, K.E., P.D. Jones., P. Ambenje, R. Bojariu, D. Easterling, A. Klein Tank, D. Parker, F. Rahimzadeh, J.A. Renwick, M. Rusticucci, B. Soden and P. Zhai, 2007: Observations: Surface and Atmospheric Climate Change. In *Climate Change 2007: The Physical Science Basis.* Contribution of Working Group I to the Forth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Ummenhofer, C.C., England, M.H., McIntosh, P.C., Meyers, G.A., Pook, M.J., Risbey, J.S., Sen Gupta, A. & Taschetto, A.S., 2009, What causes southeast Australia’s worst droughts? *Geophysical Research Letters*, 36, L04706, doi: 10.1029/2008GL036801.

Verdon, D.C. & Franks, S.W., 2006, Long-term behaviour of ENSO: Interactions with the PDO over the past 400 years inferred from paleoclimate records, *Geophysical Research Letters*, 33, L06712.

Vicbeck, M., 2009, A Station-Based Southern Annular Mode Index from 1884 to 2005, *Journal of Climate*, 22, 940-950.

Webster, P.J., Moore, A., Loschnigg, J. & Leban, M., Coupled ocean dynamics in the Indian Ocean during 1997-1998, *Nature*, 401, 356-360.

Westra, S. & Sharma, A., 2005, Dominant modes of interannual variability in Australian rainfall analysed using wavelets, *Journal of Geophysical Research*, Vol 111., doi: 10.1029/2005JD005996.

Westra, S. & Sharma, A., 2009, An Upper Limit to Seasonal Rainfall Predictability?, 32nd *Hydrology and Water Resources Symposium, Newcastle, 30th November – 3rd December 2009*.

Wheeler, M.C., Hendon, H.H., Cleland, S., Meinke, H. & Donald, A., 2009, Impacts of the Madden-Julian Oscillation on Australian Rainfall and Circulation, *Journal of Climate*, 22, 1482-1498.

Zhang, C., 2005, Madden-Julian oscillation, *Rev. Geophysics*., 43, RG2003, doi: 10.1029/2004RG000158.