Changes to Sub-daily Rainfall Patterns in a Future Climate

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This paper describes an algorithm for disaggregating daily rainfall into sub-daily rainfall 'fragments' (continuous fine-resolution rainfall sequences whose total depth sums to the daily rainfall amount) under a future, warmer climate. The basis of the algorithm is to re-sample sub-daily fragments from the historical record conditional on the total daily rainfall amount and a range of temperature-based atmospheric predictors representative of the future climate. The logic is that as the atmosphere warms, future rainfall patterns will be more reflective of historical rainfall patterns which occurred on warmer days at the same location, or at locations which have an atmospheric temperature profile more reflective of expected future conditions.

It was found that the daily to sub-daily scaling relationship varied significantly by season and by location, with rainfall patterns on warmer seasons or at warmer locations typically showing more intense rainfall occurring over shorter periods within a day compared with cooler seasons and locations. Importantly, by regressing against temperature-based atmospheric covariates, this effect was substantially reduced, suggesting that the approach may also be valid when extrapolating to a future climate. An adjusted method of fragments algorithm was then applied to nine stations around Australia, with the results showing that when holding total daily rainfall constant, the maximum intensity of short duration rainfall increased by a median of about 5% per degree change in temperature for the maximum 6 minute burst and 3.5% for the maximum one hour burst, whereas the fraction of the day with no rainfall increased by a median of 1.5%. This highlights that a large proportion of the change to the distribution of rainfall is likely to occur at sub-daily timescales, with significant implications for many hydrological systems.

1. INTRODUCTION

Understanding changes in rainfall patterns resulting from anthropogenic emissions of greenhouse gases remains an important and continuing area of research, both for scientific reasons to better constrain expected changes to the global hydrological cycle, and due to the immense societal implications of any shift in rainfall intensity or frequency [*Bates et al.*, 2008; *IPCC*, 2011]. Much of this research has focused on daily or longer-scale precipitation changes, due in large part to the availability of high-quality global land-surface precipitation datasets [*Gleason et al.*, 2002; *Klein Tank et al.*, 2002; *Peterson et al.*, 1997] to facilitate research on historical precipitation changes [e.g. *Alexander et al.*, 2006; *IPCC*, 2011]. Furthermore, there is now widespread availability of daily global climate model output as part of the CMIP3 archive [*Meehl et al.*, 2007] and upcoming CMIP 5 archive [*Taylor et al.*, 2012], with CMIP3 having been used to understand possible future changes as the atmosphere continues to warm [*Allan and Soden*, 2008; *Trenberth*, 2011].

Despite this, it is increasingly recognised that many of the physical processes of rainfall operate at much finer timescales, and that changes at the finest timescales may not be captured properly by daily total rainfall amounts. For example, it is well known that the evolution of individual convective systems occurs over timescales of hours or less, with these systems often being responsible for the highest-intensity rainfall [*Wallace and Hobbs*, 2006]. Furthermore, although rainfall is almost always caused by the upward motion of air [*Trenberth et al.*, 2003], the mechanisms which drive this upward motion are diverse and vary significantly over the course of a single day [*Evans and Westra*, 2011], with no *a priori* reason for suggesting that each of these mechanisms would change in the same manner in a future climate.

One important line of evidence in this area concerns investigations into the scaling relationship between rainfall and temperature, using historical sub-daily rainfall and atmospheric temperature data in Europe, Australia and Japan [*Berg et al.*, 2009; *Haerter et al.*, 2010; *Hardwick-Jones et al.*, 2010; *Lenderink and van Meijgaard*, 2008; *Lenderink et al.*, 2011; *Utsumi et al.*, 2011]. The basic hypothesis being tested by all these studies is that extreme rainfall will scale at a rate proportional to the moisture holding capacity of the atmosphere, which increases by about 7% per degree as governed by the Clausius-Clapeyron (C-C) relationship [*Trenberth*, 2011; *Trenberth et al.*, 2003]. The general conclusions of the abovementioned studies suggest a much more complex situation than is implied by this simple thermodynamic relationship, however, showing that the scaling is affected by:

(1) the extremity (or recurrence interval) of the rainfall event, with more extreme rainfall typically exhibiting greater scaling with temperature compared with less extreme events;

(2) the duration of the rainfall event, with hourly or sub-hourly rainfall bursts exhibiting higher scaling compared with daily rainfall;

(3) the atmospheric temperature, with [*Lenderink and van Meijgaard*, 2008] finding C-C scaling at temperatures below 12°C, and double C-C scaling at greater temperatures in The Netherlands, whereas [*Hardwick-Jones et al.*, 2010] and [*Utsumi et al.*, 2011] showed negative scaling at temperatures above about 26°C in Australia; and

(4) availability of atmospheric moisture, with the [*Hardwick-Jones et al.*, 2010] study suggesting the decline above 26°C might be attributed to insufficient moisture at these temperatures.

Despite all this complexity, a consistent result is that scaling between atmospheric temperature and sub-hourly rainfall appears to be much greater than for daily rainfall, highlighting that many of the expected changes in the future might also occur at these shorter timescales. This pattern is also borne out by several recent trend studies conducted in the diverse climates of Australia and Hong Kong and The Netherlands [*Jakob et al.*, 2011; *Lenderink et al.*, 2011; *Westra and Sisson*, 2011], which show greater trends in extreme precipitation at sub-daily timescales. The implications are that different scaling rates at different timescales would necessarily result in a shift in the temporal distribution of rainfall, from lower-intensity rainfall occurring over longer periods throughout the day to higher-intensity rainfall occurring over shorter storm bursts [*Trenberth*, 2011].

In this paper we propose a statistical downscaling algorithm which is capable of yielding continuous rainfall sequences down to the resolution of the observational network (6 minutes in the case Australia). The proposed algorithm couples daily downscaling results which can be generated using a range of downscaling techniques [e.g. *Charles et al.*, 1999; *Mehrotra and Sharma*, 2006; *Mehrotra and Sharma*, 2007] with a daily to sub-daily rainfall disaggregation algorithm that accounts for changes in future rainfall patterns. As daily downscaling of precipitation is by now a reasonably mature field and since the proposed algorithm can be coupled with a large variety of statistical and/or dynamical daily downscaling algorithms, this paper describes the disaggregation component only.

2. DATA

The continuous sub-daily rainfall data used for this study was obtained from the Australian Bureau of Meteorology (www.bom.gov.au), which maintains digitised records of sub-daily rainfall gauges throughout Australia at resolutions of 6 minutes. For this study we focus on a subset of nine gauges from this larger record, with each of these gauges having near-continuous records over the period from 1979 through to 2006. This period has been selected to ensure consistency with the reanalysis data described later.

The gauge locations are summarised in **Figure 1**, and represent a diversity of climate zones, ranging from a tropical climate in the northern parts of Australia (and in particular Cairns and Darwin), through to mid-latitude and higher latitude climates further south. The rainfall at these stations also differ substantially in terms of their seasonal patterns, with the two tropical stations of Darwin and Cairns being summer-dominated, having majority of the rainfall occur from November through to April, whereas Perth and Adelaide have climates which are winter dominated, with most of the rain falling during the period from May through to October. The remaining stations have rainfall distributed more evenly throughout the year.

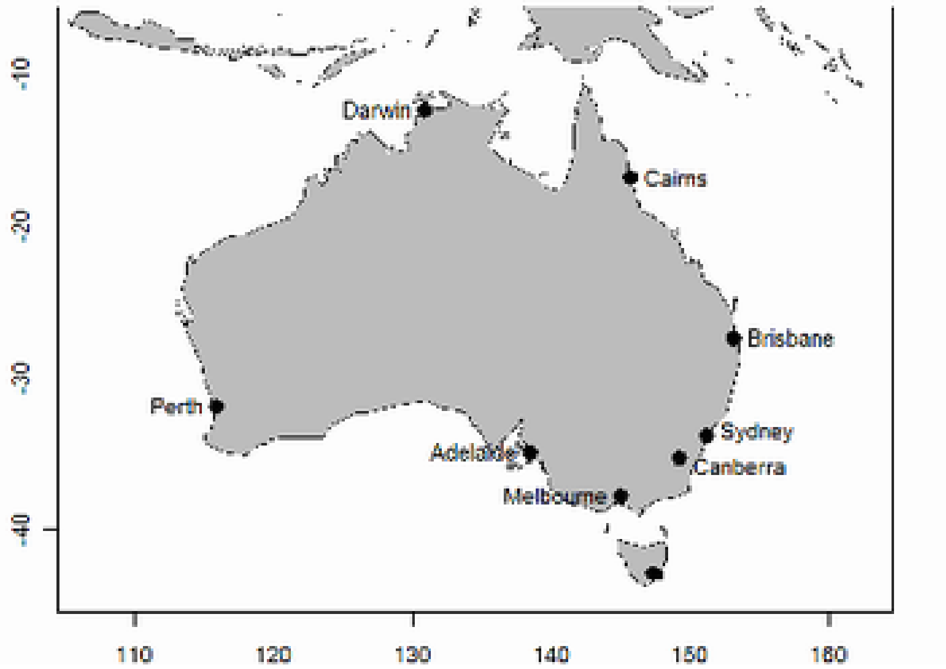

Figure 1: Map of Australia with location of gauges used for the analysis.

At each gauge location, a range of atmospheric variables were extracted using the NCEP Climate Forecast System Reanalysis (CFSR) product, which is described at length in Saha *et al* [2010]. The data is available from 1979 to present, at a grid spacing of 0.5° x 0.5° longitude and latitude. The data was downloaded at an hourly temporal resolution, and was originally produced through a combination of short forecasts (the guess field), modified by assimilating new observations every six hours.

Table 1: Summary of variables extracted from the CFSR reanalysis at the grid point closest to the station locations in Figure 1.

Variable	Abbreviated name	Daily mean, maxima, minima and/or diurnal range	Units
2m surface temperature	tmp2m	mean, maxima, minima, range	Degrees Celsius
500, 700 and 850hPa temperature	t500, t700, t850	mean	Degrees Celsius
Dew point temperature	Td	maxima	Degrees Celsius
Relative humidity	RH	mean and maxima	Percentage (%)
Pressure reduced to mean sea level	prmsl	mean and minima	Pa
850hPa wind strength and direction	wnd850_str, wnd850_theta	mean	(derived from *u* and *v* components of wind; units of m/s)
10m wind strength and direction	wnd10m_str, wnd10m_theta	mean	(derived from *u* and *v* components of wind; units of m/s)
500 and 850hPa geopotential height	z500, z850	mean	Geopotential meter (gpm)

3. METHOD

A generalised additive modelling (GAM) framework was adopted to model the relationship between metrics of daily to sub-daily scaling, namely the fraction of rain falling in the maximum 6 minute and 1 hour storm bursts and the fraction of a wet day with no rainfall, and the atmospheric predictors described in **Table 1.** These scaling metrics were selected as part of the development of a daily to sub-daily rainfall disaggregation algorithm described in [*Westra et al.*, 2012], and the reader is referred to that paper for more information.

Generalised additive models were first developed by [*Hastie and Tibshirani*, 1986], and a textbook length treatment is provided in [*Wood*, 2006]. The latter reference was used as the basis for the analysis of this paper, and the R software package [www.r-project.org] `mgcv` which accompanies the reference was used for the implementation of the GAM. The benefits of GAMs are that they provide an extremely flexible modelling structure which allows the response variable to depend on a sum of smooth functions of predictor variables, while also allowing the distributional assumptions of the response variable to follow any distribution from the exponential family. The general expression for a GAM is given as [*Wood*, 2006]:

$$g(\mu) = \mathbf{X}^*\boldsymbol{\theta} + f_1(x_1) + f_2(x_2) + f_3(x_{3,} x_{4,})$$

where

$\mu = \mathbb{E}(Y)$, and Y ~ an exponential family distribution

Here **X*** represents the model matrix of parametric components, **θ** is the parameter vector, and the f_j are smooth functions of covariates *x*. Thus this modelling framework allows for the simulation of linear components as well as smooth functions, and by specifying smoothing functions in more than one dimension, interactions between covariates can be simulated. Factor variables, in which variables are grouped into different levels such as by rainfall gauge location, can also be accommodated into the method by using dummy indicator variables within the linear component of the model.

4. RESULTS

4.1. Importance of atmospheric temperature in influencing the daily to sub-daily scaling of rainfall

We commence by examining the impact of seasonality on three measures of daily to sub-daily scaling: the fraction of daily total rainfall occurring in the maximum 6 minute and 1 hour storm bursts, and the fraction of each wet day with no rainfall. These variables are the response variables which we wish to simulate as a function of atmospheric covariates, and the question posed in this paper is the extent to which temperature-based atmospheric variables have an influence on the behaviour of these response variables.

We start by simulating these response variables using the day of the year as the covariate. This allows simulation of the seasonal behaviour of the daily to sub-daily scaling relationship, with an *a priori* expectation based on the literature reviewed previously that for a given daily rainfall amount, we would have more rainfall occurring in a shorter period, such that the rainfall when it occurs is more intense. The results using the maximum 6 minute rainfall are shown in **Figure 2**, for all the stations used in this analysis except Adelaide. Adelaide was not included as it was found not to have the day of the year as a significant predictor. The results for the remaining stations indeed agree with this general conclusion, with all stations except for Darwin showing much greater fraction of the total daily rainfall occurring in the maximum 6 minute burst during the warmer summer months compared with winter. In the case of Darwin, due to the tropical nature of the climate in this location, there is limited seasonal variation in atmospheric temperature, but a significant difference in moisture availability, and it is likely that this factor is responsible for the opposite relationship. The analysis was repeated on the fraction of daily rainfall occurring in the maximum 1 hour burst, as well as the fraction of the day with no rainfall, and consistent results were obtained (not shown).

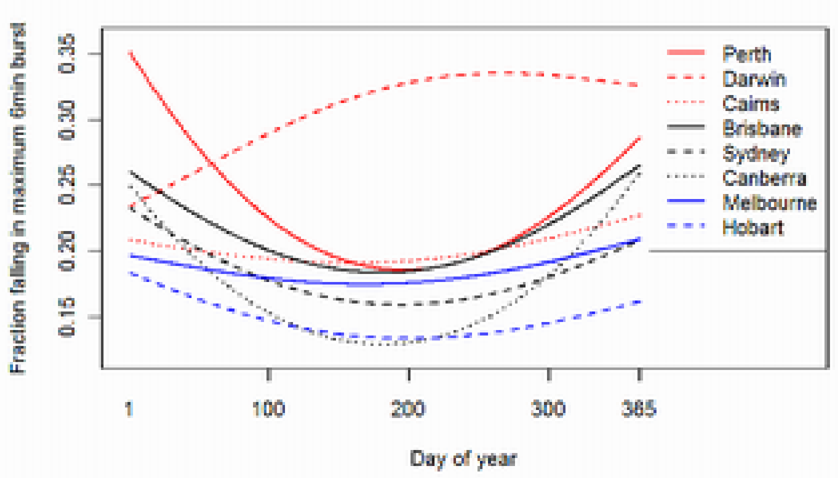

Figure 2: Seasonal variation in the fraction of daily rainfall occurring in the maximum 6 minute rainfall burst.

We now examine the extent to which this seasonality can be expressed as a function of atmospheric temperature. We therefore model the relationship of each of the response variables as a function of both the day of the year and the temperatue on that day, to determine the influence of both covariates. This is shown in the case of the fraction of the daily rainfall occurring in the maximum 6 minute burst in **Figure 3**, and once again consistent results were found for the remaining covariates.

The results are presented as a contour plot for each station, with the contours representing the fraction of daily rainfall occurring in the maximum 6 minute storm burst. In almost all cases the results show much stronger gradients in the direction of temperature, and smaller gradients in the direction of the day of year, highlighting that most of the seasonal variation in the daily to sub-daily scaling is accounted for by the single metric of daily temperature. These results are consistent with the results of [*Beuchat et al.*, 2011], who also found a significant relationship with temperature. In our case, for Sydney, Brisbane and Hobart the effect of seasonality has been almost entirely eliminated, whereas for Perth and Melbourne the seasonal cycle becomes somewhat obscured and no longer clearly interpretable, with the minima in both locations occurring around day 250 (September) and a local maxima for Perth around June/July, whereas for Melbourne the fraction of rainfall falling as the maximum 6 minute burst is greater in mid-winter than for late December/early January. Similarly, Canberra shows its minima in late spring, which no longer reflects the seasonality shown in **Figure 2**. Once again since the day of year was not significant for Adelaide, the results for Adelaide were therefore not shown.

Finally, we examine the extent to which the different daily to sub-daily rainfall scaling relationships at each location can be accounted for by atmospheric temperature. This is done by setting up a GAM as a function of three predictors: the station (represented as a factor variable in the model), the maximum daily temperature, and the daily total rainfall amount. This latter variable was included as a predictor because of the significant difference in total daily rainfall between the different stations, and the fact that the proportion of rain falling in the maximum 6 minute storm burst itself varies with daily rainfall [*Westra et al.*, 2012]. The results are then presented: (a) conditional to the maximum daily temperature averaged at *each* station; and (b) conditional to the maximum daily temperature averaged *across all* the stations. The daily rainfall was held at the average across all stations to eliminate the effect of variability in this predictor on the results.

The results are shown in **Figure 4** together with error bars representing ± two standard errors from the point estimate. As can be seen from this figure, the upper panel, which represents the results conditional to maximum temperature averaged at each station, shows a large range in the scaling relationship, with Darwin having the largest fraction of rainfall occurring in the maximum 6 minute burst and Hobart having the smallest, and with the remaining stations showing intermediate values ranked approximately according to their latitude and mean atmospheric temperature.

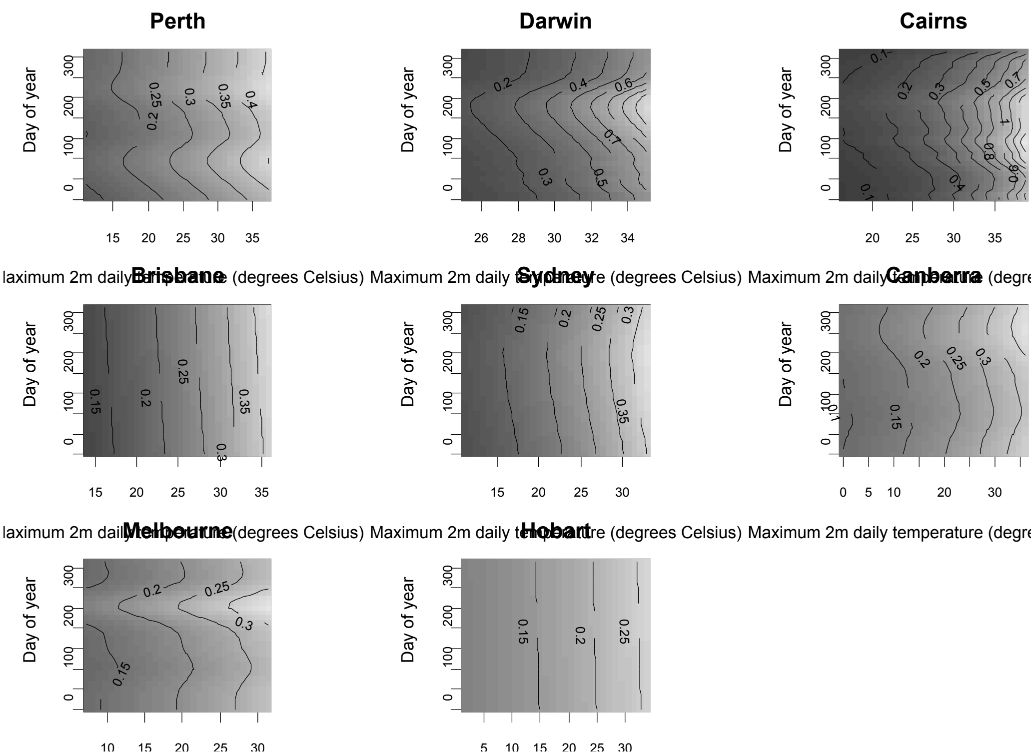

Figure 3: GAM surface of fraction of rainfall occurring in the maximum storm burst, plotted against 2m daily temperature (x axis) and the day of the year (y axis).

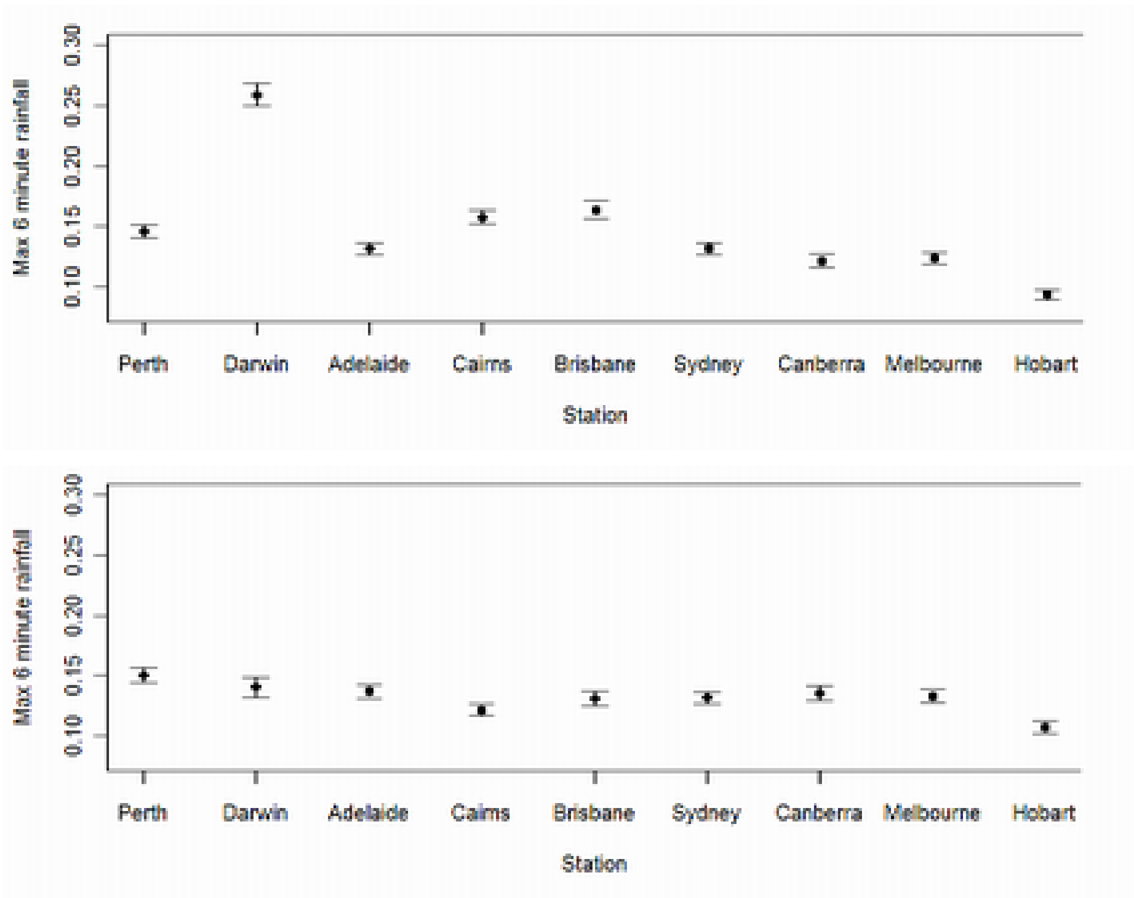

Figure 4: Fraction of rainfall occurring in the maximum six minute storm burst as a function of the station, with the atmospheric temperature set at the mean at each station (upper panel) and mean across all stations (lower panel).

In contrast when looking at the results conditional to the maximum daily temperature averaged across all locations (approximately 20°C; lower panel of **Figure 4**), the results show a much more consistent response, with most of the point estimates being within the confidence intervals of the other locations. Furthermore, the change in the scaling relationship no longer shows any obvious relationship with latitude, with Hobart still having the lowest scaling relationship but with Cairns showing the second lowest, whereas mid-latitude Perth has the highest scaling relationship. The convergence in the daily to sub-daily rainfall scaling relationships by conditioning on the same atmospheric temperature at each location is a remarkable result, given the distinct climatology and seasonality of each region, and once again adds support to the hypothesis that much of the information on daily to sub-daily scaling relationships can be accounted for by a small subset of atmospheric predictors.

4.2. Sensitivity of the scaling relationship as a function of atmospheric temperature

In the previous section the impact of atmospheric temperature on daily to sub-daily scaling of rainfall was explored, and it was found that much of the variability between seasons and between stations with different climatologies can be largely accounted for by a single predictor representing atmospheric temperature. We now develop a model including a greater number of temperature-based covariates were used from the reanalysis data, including (1) the mean, daily maximum, daily minimum and daily range of 2m surface temperature; (2) the mean 500, 700 and 850hPa temperature; and the maximum dew point temperature. This latter covariate was included because it also accounts for moisture available, which as suggested by [*Hardwick-Jones et al.*, 2010] and other studies, may play an important role in influencing the intensity of sub-daily rainfall extremes.

Having identified a range of plausible models relating attributes of daily to sub-daily rainfall scaling to atmospheric covariates, we now test the implications of changing these covariates to understand the sensitivity of the scaling relationship. We once again focus on the relationship between the daily rainfall and the fraction of rain falling in the maximum 6 minute storm burst. We evaluate the sensitivity to the covariates by increasing each of the atmospheric temperature variables by a specified amount while holding all other variables constant, and then estimating the change in the response.

The results of this analysis are summarised in **Figure 5a**, using the `mgcv` predictor selection algorithm. Referring firstly to the temperature-only covariates, there was an increase in the fraction of rainfall occurring in the maximum 6 minute burst by an average of between about 2% (Melbourne) and 8% (Cairns) per degree change in atmospheric temperature, with a mean of 5% per degree across all the stations. This also implies a corresponding decrease in the rain falling throughout the rest of the day, expressed either as a lower rainfall intensity during the remainder of the day or as a greater proportion of the day being dry.

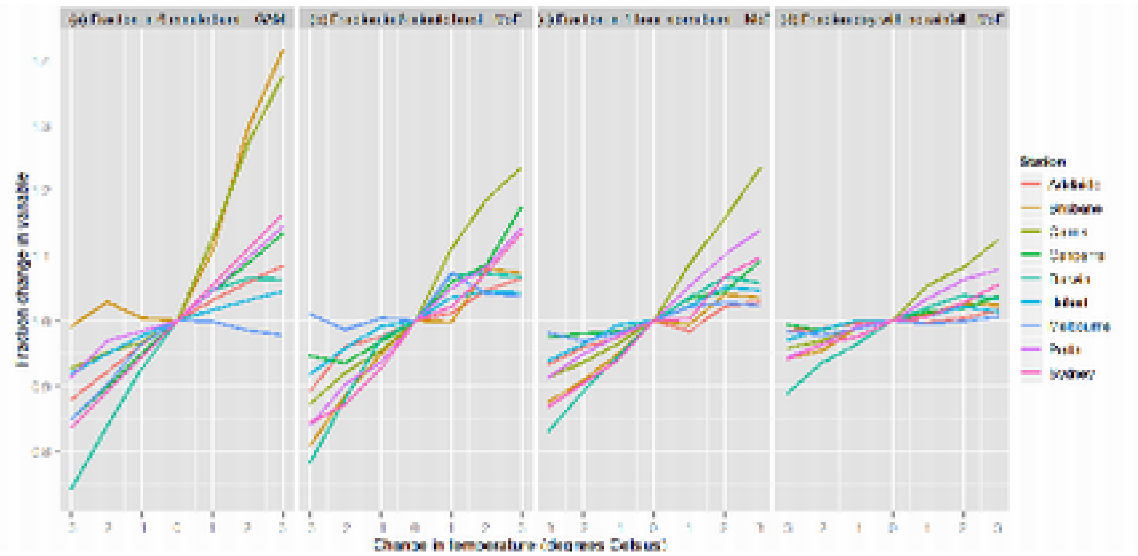

Figure 5: Change in different metrics of daily to sub-daily scaling as a function of changes in atmospheric temperature, simulating directly from the fitted GAM (left panel) or extracted after running the method of fragments approach but conditionally sampling on different atmospheric temperatures. Results using temperature-only covariates.

Although this approach is able to provide insight into the fraction of rainfall occurring in the maximum 6-minute burst, the rainfall pattern for the remainder of the day is lost. Given that flood estimation practice and the design of storm water systems are increasingly reliant on knowledge of the full distribution of rainfall, we propose a modification to the daily to sub-daily rainfall disaggregation algorithm known as the Method of Fragments (MoF), which searches through the historical record for rain days which are 'similar' to the day of interest as the basis to re-sampling. This algorithm was described at length in [*Mehrotra et al.*, 2012; *Westra et al.*, 2012] for the situation of stochastically generating rainfall under a historical climate, in which sub-daily fragments (i.e. continuous sequences of rainfall at 6 minute resolution spanning a 24 hour period) were selected at 'nearby' locations conditional on daily rainfall, with 'nearby' defined in terms of physiographic measures of longitude, latitude, elevation and distance to coast.

To account for anthropogenic climate change, we modify this algorithm by, rather than using physiographic covariates, sampling sub-daily fragments conditional to atmospheric predictors. This modification is justified based on the research in the previous section (and in particular Section 3.2), in which it was found that changes in the scaling relationship during different seasons or at different locations could be explained by atmospheric covariates such as temperature.

In the context of a sensitivity analysis, the proposed algorithm uses a generalised additive modelling framework as the basis for re-sampling, and is described by the following algorithm:

(1) For all wet days during the historical record, store the values of each of the atmospheric covariates using the reanalysis data, and for each day use the fitted GAM to predict one of the measures of daily to sub-daily scaling such as the fraction of daily rain falling in the maximum 6 minute burst.

(2) Say we wish to simulate a series with an increase of 1°C atmospheric temperature. Then for a given wet day of interest, use GAM to predict the daily to sub-daily measure using the atmospheric variables for that day, but with the temperature variables increased by 1°C.

(3) Using the predicted daily to sub-daily measure in step (2), rank all the days in step (1) by proximity to this measure. Then for a deterministic model select the 'fragment' from the lowest ranked day, or for a stochastic model select the low ranked days randomly, with the highest probability for the lowest ranked station [see equation 2 in *Westra et al.*, 2012].

The results are presented panels (b) through (d) in **Figure 6**. Even though the daily to sub-daily scaling metric used here was the fraction of daily rain falling in the maximum 6 minute storm burst, the output from the proposed MoF algorithm gives the full sub-daily sequence for each wet day, such that this hybrid GAM-MoF algorithm can be used as the basis for continuous rainfall simulation. To evaluate how a change in atmospheric temperature impacts on sub-daily rainfall, we present summary statistics for the fraction of rainfall occurring in the maximum 6 minute and 1 hour bursts, and the fraction of day with no rainfall.

Considering firstly the fraction of rain falling in the maximum 6 minute burst, we are able to compare the results from the hybrid GAM-MoF approach to obtaining predictions directly from the GAM, and find the results to be fairly comparable, although the GAM-MoF scaling is slightly less sensitive to temperature compared with the GAM-only scaling. For example, the mean sensitivity was found to be 4.1% using only the temperature covariates compared with 5% using the GAM directly. Considering the remaining metrics, the fraction of rainfall occurring in the maximum 1 hour burst has a scaling which is about two thirds the scaling for the maximum 6 minute burst, while fraction of day with no rainfall only decreases by about 1.5% per degree change in temperature for the temperature-only covariates. This suggests that although the full distribution of sub-daily rainfall is expected to change as a result of anthropogenic climate change, the greatest sensitivity is for the intensity of rainfall over very short timescales.

5. DISCUSSION AND CONCLUSIONS

This paper provides a framework for the disaggregation of daily rainfall to sub-daily rainfall fragments, which can be estimated for any temporal resolution of interest provided that historical records are available at that same resolution. In Australia, the sub-daily data was digitised at a resolution of 0.1 hour (6 minutes), and thus this was the finest resolution considered here. Conceptually the algorithm presented in this paper can be made to work at any location for which adequate sub-daily rainfall is available, and this can potentially be generalised to any location regardless of the availability of sub-daily information using adaptations described in [*Westra et al.*, 2012] and [*Mehrotra et al.*, 2012].

The basis of the algorithm is that the scaling relationships between daily and sub-daily rainfall can somehow be accounted for simply by knowing the daily rainfall amount, and the historical and future values of a set of atmospheric predictors. As discussed in the introduction, it is difficult to 'validate' any downscaling model given the limited temperature changes over the historical record compared with what is projected in the future. As an alternative, we hypothesise that if the daily to sub-daily scaling relationship – which is known to vary seasonally and from one location to another - can be accounted for largely by the atmospheric covariates, then this suggests that future changes in daily to sub-daily scaling as a result of climate change can also be described by changes in these covariates. This hypothesis was found to be reasonable using three metrics of daily to sub-daily scaling, with almost all the seasonality eliminated at many of the locations, and the scaling relationships at very climatologically different locations such as Darwin and Hobart found to converge substantially after accounting for atmospheric temperature.

We examined different GAM structures, and found that reasonable model performance occurred when considering only daily rainfall amount and a set of atmospheric temperature-based covariates. The sensitivity to a change in atmospheric temperature was then evaluated by adjusting all the atmospheric temperature covariates by between -3°C and +3°C, and then calculating the average change in daily to sub-daily scaling metrics per degree temperature change. The sensitivity was found to be highest for the shortest duration rainfall, of about 5% per degree using the temperature-only covariates. The conclusion that the intensity of the shortest-durations rainfall events will increase as temperature increases appears to be robust for a wide range of choices of covariates, although the absolute magnitude of the change varied depending on the model specification.

Finally, we demonstrated the extension to the Method of Fragments logic to disaggregate daily rainfall under a future climate. The algorithm uses the fitted GAM as the basis for selecting days with 'similar' atmospheric covariates compared to what is expected in the future, and this was trailed through a sensitivity assessment by changing atmospheric temperature while holding all the other atmospheric covariates constant. The results were found to be consistent with using the GAM directly, with the benefit of using the disaggregation logic being that the full distribution of rainfall over the course of the day can be simulated. In this case only the fraction of rain falling in the maximum 6 minute and 1 hour bursts, and the fraction of the day with no rainfall, were evaluated. However, a diversity of other sub-daily rainfall statistics can easily be assessed as well, including information of other storm burst durations, the temporal pattern, and information on the diurnal cycle of rainfall.

Finally, in the future, we intend to incorporate other atmospheric covariates which are not based on atmospheric temperature, as well as coupling the disaggregation algorithm described here with a daily downscaling algorithm, to develop projections for sub-daily rainfall under a future climate.

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