Simulating sub-daily Intensity-Frequency-Duration curves in Australia using a dynamical high-resolution regional climate model

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Abstract

Climate change has the potential to significantly alter the characteristics of high-intensity, short-duration rainfall events, potentially leading to more severe and more frequent flash floods. Research has shown that future changes to such events could far exceed expectations based on temperature scaling and basic physical principles alone, but that computationally expensive convection-permitting models are required to accurately simulate sub-daily extreme rainfall events. It is therefore crucial to be able to model future changes to sub-daily duration extreme rainfall events as cost effectively as possible, especially in Australia where such information is scarce. In this study, we seek to determine what the shortest duration of extreme rainfall is that can be simulated by a less computationally expensive convection-parametrizing Regional Climate Model (RCM). We examine the ability of the Conformal Cubic Atmospheric Model (CCAM), a ~10 km high-resolution convection-parametrizing RCM, to reproduce sub-daily Intensity-Frequency-Duration (IFD) curves corresponding to two long-term observational stations in the Australian island state of Tasmania, and examine the future model projections. We find that CCAM simulates observed extreme rainfall statistics well for 3-hour durations and longer, challenging the current understanding that convection-permitting models are needed to accurately model sub-daily extreme rainfall events. Further, future projections from CCAM for the end of this Century show that extreme sub-daily rainfall intensities could increase by more than 15 % per °C, far exceeding the 7 % scaling estimate predicted by the Clausius-Clapeyron vapour pressure relationship and the 5 % scaling estimate recommended by the Australian Rainfall and Runoff guide.

Keywords

sub-daily rainfall; extremes; Intensity-Frequency-Duration; Depth-Duration-Frequency; flood; RCM

1. Introduction

Heavy rainfall events with durations of less than 24 hours are a triggering factor for many high-impact natural hazards, including flash floods, landslides and debris flows. These hazards pose significant risk to people, infrastructure and systems. Climate change has the potential to alter both the prevalence and severity of rainfall extremes and floods (Bates et al., 2016), with intensification of heavy rainfall events becoming evident in the observed record across many regions of the world (Fischer and Knutti, 2016), necessitating an improved understanding of how they may change in the future.

Dynamical Regional Climate Models (RCMs) have been used to produce estimates of the future changes to more extreme, multi-day rainfall events across Australia (e.g. White et al., 2013; Perkins et al., 2014; Evans et al., 2016; Li et al., 2016; 2017). There exists, however, considerable uncertainty in future extreme rainfall projections, particularly for the sub-daily intensities (Johnson et al., 2016). To date, few studies have examined sub-daily rainfall extremes in Australia. This paucity of studies is due to a combination of sparse observations, the inability of broad-scale Global Climate Models (GCMs) to reliably simulate sub-daily rainfall (Chan et al., 2014b), and the costs associated with high-resolution climate modelling. Variations in frequency and magnitude of observed events at daily durations have also been found to be a poor indicator of changes at sub-daily durations (Jakob et al., 2011); as such, multi-day rainfall projections cannot be directly used to inform changes in sub-daily-duration rainfall. Yet it is these short duration rainfall intensities that are of particular interest to practitioners and decision-makers who require reliable design-rainfalls for runoff studies, either for mitigating the potential damage to existing infrastructure or adapting to the future (Bates et al., 2016).

While recent progress has been made towards understanding and modelling hourly rainfall intensities internationally (notably Lenderink and van Meijgaard (2008) for the Netherlands, Kendon et al. (2012) and Chan et al. (2014a; 2014b; 2016) for the UK, and Sunyer et al. (2017) for Denmark), there is a paucity of both sub-daily rainfall observations and climate change projections across Australia. Although there is an extensive record of daily rainfall observations available from the Bureau of Meteorology (BoM), spanning several decades – and in some cases, over 100 years in length – high-quality sub-daily (e.g. 6-min continuous) rainfall observations from pluviographs or Tipping Bucket Rain Gauges are far more limited, with such data often much shorter in length (typically with a record of less than 25 years). To adequately sample the effects of climate variability on rainfall extremes long, homogeneous time series are required (Jakob et al., 2011). Due to these limitations there have been few studies of these continuous sub-daily observations to date (see Jakob et al. (2011) and Zheng et al. (2015) for studies of trends in sub-daily rainfall durations in the Sydney region, where sub-daily rainfall trends are found to differ from multi-day trends). Because of the limited spatial availability of sub-daily observations, no gridded sub-daily rainfall product exists for Australia, making the evaluation of modelled sub-daily rainfall extremes a significant challenge (Rummukainen et al., 2015).

The Australian Rainfall and Runoff (ARR) (Ball et al., 2016) is the main guide used by Australian engineers and hydrologists to combine statistical methods and observations to estimate return levels and design rainfalls. The 2016 revision of ARR includes new Intensity-Frequency-Duration (IFD) curves suitable for the current climate across Australia (Bates et al., 2015; Bureau of Meteorology, 2016)[1]. These curves were generated using a quality-controlled homogenised database comprising rainfall data from the BoM's rain gauge network and data from rainfall recording networks operated by other organisations (Green et al., 2012; 2016). In the absence of spatially and temporally consistent sub-daily and multi-day future rainfall projections, interim guidance has been provided to allow for a range of plausible future changes to rainfall to be applied to the IFD curves (Bates et al., 2016). Uncertainty in broad-scale GCM rainfall projections is, however, generally high; Bates et al. (2016) suggest using 5 % as the default percentage change in heavy rainfalls per °C of warming but note that this could in reality be between 2 % and 15 % per °C of warming. As such the ARR approach uses a simple adjustment factor of 5 % per °C of warming, based on projected temperature increases from a consensus of GCM simulations for a given future realisation (or 'class interval') of 'slightly warmer' (< 0.5 °C), 'warmer' (0.5 to 1.5 °C), 'hotter' (1.5 to 3 °C) or 'much hotter' (> 3 °C). This method applies a corresponding regional correctional value to the IFDs producing a projected increase in rainfall intensity.

This method used in ARR is based on the understanding that daily rainfall increases with temperature at a rate of approximately 7 % per °C according to the Clausius-Clapeyron water-holding capacity relationship between temperature and vapour pressure (Trenberth et al., 2003). In contrast to daily cumulative rainfall it has been found that daily and sub-daily heavy rainfall intensities do not consistently follow the Clausius-Clapeyron relationship due to the additional latent heat released from increased atmospheric moisture (Lenderink and van Meijgaard, 2008;

[1] It should be noted that the name for Intensity-Frequency-Duration curves varies by country. In the United States, for example, they are more commonly referred to as Depth-Duration-Frequency curves.

Liu et al., 2009). Liu et al. (2009) found that global average daily rainfall intensity increases by about 23 % per °C, significantly exceeding the ~7 % per °C from the Clausius-Clapeyron relationship. At the sub-daily timescale, Lenderink and van Meijgaard (2008) found that the observed intensity of hourly rainfall extremes at a station in the Netherlands increases twice as fast per °C as expected from the Clausius-Clapeyron relationship when daily mean temperatures exceed 12 °C. This observed trend was matched in the same study by simulations using a high-resolution regional climate model showing that one-hour extreme rainfall intensities increase at a rate close to 14 % per °C of warming across large parts of Europe. By using medium- and high-resolution RCMs, Chan et al. (2014a) similarly found that future extreme hourly rainfall intensities in the southern UK cannot simply be extrapolated using a present-climate temperature scaling approach.

Dynamical climate models need to be of sufficient resolution to capture the large-scale influences of various climate modes, the diurnal and seasonal cycles, and the regional and local scale convection-permitting and orographic wind processes that are the proximate cause of extreme rainfall (Westra et al., 2014; Rummukainen et al., 2015; Cortés-Hernández et al., 2016; Johnson et al., 2016; Kendon et al., 2017). Lower-resolution dynamical models, for example, have been shown to contain large rainfall biases (Kjellström et al., 2010), poor timing and durations (Brockhaus et al., 2008), and inaccurate spatial distributions (Gregersen et al., 2013). Spatial model resolution also influences the quality of the representation of dynamical rainfall projection, especially for extremes over short timescales that are more likely to be dominated by convection (Chan et al., 2014b; Sunyer et al., 2017). Although statistical downscaling methods for hydrological applications exist (e.g. Willems and Vrac, 2011), it is only higher-resolution dynamical climate models that can likely simulate this temperature-rainfall relationship (Ban et al., 2014).

High-resolution (~10 km grid) dynamically downscaled climate change simulations have been produced for Australia's island state of Tasmania using a convection-parametrizing RCM by the *Climate Futures for Tasmania* project (Corney et al., 2010; 2013). These simulations – the most recent high-resolution regional climate projections for Tasmania – have been extensively analysed for a range of extremes including rainfall, projecting increases in maximum 1- and 5-day rainfall intensities separated by longer dry spells (White et al., 2010; 2013). Projections for Hobart and Launceston – the two most populous areas of the state – suggest that the 1 % Annual Exceedance Probability (AEP) intensity for 24-hour duration rainfall totals will increase by about 25 % in both locations by the end of the Century (White et al., 2010). These previous studies, however, primarily rely on daily rainfall values. As a consequence, we therefore have limited understanding of how the projected changes in daily rainfall across Tasmania translate to sub-daily intensities.

As part of the *Climate Futures for Tasmania* project, a multi-model high-resolution 6-minute dataset was produced at 14 discrete locations across Tasmania, corresponding approximately to the high-quality BoM network stations distributed across the state. In this study, we use these continuous 6-minute simulations for the first time to generate IFDs at the main population centres of Hobart and Launceston. The objective of this study is to test how an RCM simulates a range of sub-daily design rainfall intensities compared to observed values covering the overlapping observed period (1961-2014), and to assess whether the simple temperature scaling allowance for climate change recommended in the ARR 2016 interim guide is appropriate for all rainfall durations and intensities. We seek to find the shortest duration of extreme rainfall events that is accurately simulated by our convection-parametrizing RCM, in order to find the limit of applicability of these types of models.

This paper is outlined as follows: section 2 details the models, observations, and analytical methods used in this study, section 3 examines the models' ability to reproduce observed extreme rainfall statistics, section 4 examines the models' projections for the future, and section 5 provides a discussion.

2. Materials and methods

2.1 Study area

Tasmania, an island state southeast of the Australian continental landmass, sits within the westerly wind belt of the Southern Hemisphere. Launceston Airport and Hobart were selected as study locations in Tasmania as they represent the two most populous areas of the state and both have long-term pluviograph records. Both sites are at least somewhat sheltered from the prevailing westerlies by the orography of the western half of Tasmania. Hobart lies at the mouth of the Derwent River in southeast Tasmania, experiencing a mean rainfall of approximately 50 mm per month. For most of the year, rainfalls are due to the passage of cold fronts in the westerly airstream. Hobart's highest daily rainfalls, however, tend to occur during occasional east to southeasterlies associated with extratropical cyclones, where upwards of 50 mm can fall in a single day. Launceston Airport lies in the northwest-southeast oriented Tamar Valley, with the valley defined by the Tasmanian Central Plateau to the west and northeast highlands to the east. Monthly rainfall for Launceston Airport ranges from 40 mm in late summer to 80 mm in winter. This site is more exposed to moist northwesterly airstreams associated with broad troughs and, particularly, the cold frontal systems often embedded in such troughs. These unstable northwesterly airstreams provide Launceston Airport with its highest daily rainfalls, and many of its most intense sub-daily rainfall totals. Remaining sub-daily intense rainfalls do occasionally occur in weakly forced synoptic situations, generally during the warm season in slow-moving thunderstorms.

This study has two parts: a comparison between observed data and modelled data for 1961-2009; and a comparison between modelled data for 1961-2009 with modelled data for 2070-2099. We first examine the annual maximum (AMAX) timeseries for each of the two comparisons, and then use this AMAX data to examine the IFD relationships for each comparison. Tasmania, like much of south-east Australia, has experienced a decrease in rainfall since 1975 (Gallant et al., 2007). Across Tasmania there was no statistically significant trend in mean annual rainfall between 1910 and 1990 (Srikanthan and Stewart, 1991); however, there has been a downward trend in rainfall between 1970 and 1995 (Shephered, 1995). Across south-east Australia there has been a slight downward trend in rainfall between 1910 and 2005 (Gallant et al., 2007). Future projections of rainfall for Tasmania indicate a change in mean annual rainfall of less than 100 mm between 1961 and 2100 (Grose et al., 2010), although note that this result conceals more significant changes at seasonal and regional scales (Grose et al., 2013). We use 1961-2009 as the "current climate" period to maximise the overlap between observations and our model output. By using this longer time period we maximise the number of observational data points used in the analysis, thus reducing the opportunity for bias.

2.2 Observed data

The observed rainfall data for this study were recorded using Tipping Bucket Rain Gauges (TBRG) at two locations, Hobart Ellerslie Road (station number 94029) and Launceston Airport (station number 91104). These datasets are in the form of six-minute rainfall totals, collected using digitized pluviograph records from a Dines Tilting Siphon Rain Gauge, and obtained from the Bureau of Meteorology (BoM).

Both sites contain a large amount of missing data. For Hobart, 58 % of the observed data is missing, and for Launceston, 65 % of the observed data is missing (in both locations, for the 1961-2009 time period examined in this study). The distribution of the missing data is assumed to be random, as it occurred due to missing and/or degraded paper pluviograph records without any particular temporal pattern. There are no significant gaps in the timeseries; rather, missing data occurs randomly throughout the entire time period.

The observed data is put through a two-step quality control process to minimize any erroneous observations. First, any individual six-minute observations with greater than 20 mm of rainfall are ignored. While observations of greater intensity have occurred globally, this is above the range reliably observed in Tasmania. Second, the total of all six-minute observations over each day is compared to the corresponding 24-hour datum, which was recorded with a different device. For any days where the sum of the six-minute observations differs from the corresponding 24-hour observation by more than 20 % and simultaneously by at least 5 mm, the observations from the entire day are ignored. In summary, for Hobart, the observed data we start with for 1961-2009 has 1,802,191 valid observations (not counting missing data), and after quality control we end up with 1,800,030 observations that we use in the study. For Launceston, we start with 1,493,457 valid observations, and after quality control we end up with 1,489,617 observations that we use in the study.

2.3 Modelled data

The modelled data for this study is obtained from the *Climate Futures for Tasmania* project. The methods are described in full in Corney et al. (2010), and are summarized here.

The *Climate Futures for Tasmania* project used the Conformal Cubic Atmospheric Model (CCAM) from Australia's CSIRO research organisation (McGregor and Dix, 2001; McGregor, 2005; McGregor and Dix, 2008). CCAM is a global atmospheric model that uses a stretched cubic conformal grid utilising the Schmidt transformation (1977) with higher resolution in areas of interest (Tasmania). The grid has a resolution of ~10 km per grid cell over the primary face (covering Tasmania) with variably lower resolution over the remainder of the globe. As CCAM is an atmospheric RCM, it is forced by sea surface temperature (SST) as the bottom boundary condition. CCAM uses a semi-Lagrangian advection scheme and semi-implicit time integration with an extensive set of physical parameterizations in a hydrostatic formulation. The GFDL parameterizations for long-wave and short-wave radiation (Lacis and Hansen, 1974; Schwarzkopf and Fels, 1991) were used, with interactive cloud distributions determined by the liquid and ice water scheme of Rotstayn (1997). The simulations used a stability-dependent boundary layer scheme based on Monin-Obukhov similarity theory (McGregor et al., 1993). CCAM's cumulus convection scheme with both downdrafts and detrainment, as well as mass-flux closure, is described by McGregor (2003). Six different GCMs were used to force CCAM to produce the model output used for this study, as described in Table 1.

The dataset used for the current study is the timeseries of rainfall data from CCAM for the SRES A2 high emissions scenario (Nakićenović et al., 2000), with a temporal resolution of 6 minutes. Only data from two grid points is used: the grid point closest to the Hobart Ellerslie Road meteorological station and the grid point closest to the Launceston Airport meteorological station (described above). It should be noted that the elevation of these grid points in the CCAM model is the average elevation over their respective 10 km grid squares, which is different from the actual elevation of the meteorological stations. For the Hobart station, the elevation of the modelled grid point is approximately 150 m higher than the actual elevation of the station, since this grid square contains the lower slopes of Mount Wellington (elevation 1271 m). For the Launceston station, the elevation of the modelled grid point and the elevation of the station are approximately the same, as the landscape is fairly flat near this station. These two locations, Hobart and Launceston Airport, are chosen because they have the most complete observed datasets.

2.4 IFD curves

After the timeseries of 6-minute rainfall totals is obtained for each dataset and for each location (observed 1961-2009, modelled 1961-2009, and modelled 2070-2099), the rainfall totals over varying durations are calculated. These durations are 0.5, 1, 3, 6, 12 and 24 hours. The rainfall totals for each duration are found using a method of rolling sums, such that for each 6-minute observation, the total rainfall over the past *x* hours is found, where *x* is the duration of rainfall being examined. Thus, the dataset of rainfall totals for each duration (e.g. 1-hour totals) is the same length as the original six-minute dataset. Frequency distribution plots, shown in the Appendix (Fig. A.1 and A.2), serve as the most basic representation of the results. To create these frequency distribution plots, the rolling sum data for each dataset is collected into 150 evenly spaced bins, selected based on the minimum and maximum values of the data.

To create the IFD curves, the timeseries of annual maximum rainfall values (AMAX) is found for each dataset and these are fitted to a Generalized Extreme Value (GEV) distribution. A sample of these fits (3- and 6-hour durations) is shown in the Appendix (Fig. A.3 to A.6). For each of six annual exceedance probabilities (AEPs 1, 2, 5, 10, 20, and 50 %), the corresponding intensity is found using the fitted GEV distribution. This calculation is repeated for each rainfall duration (i.e. 0.5-hour, 1-hour, etc.) and the intensities are plotted. Finally, for each of the six modelled IFD curves, the multi-model mean intensity value is used, with the multi-model min and max values used to estimate the spread of plausible futures presented by the different GCMs.

2.5 Assessing modelled IFD curves

The ARR guidelines are the Australian industry standard methods for flood estimation. These guidelines were last updated in 2016 (see Ball et al., 2016) and have a recommended approach to incorporate the influence of climate change on flood estimates. ARR suggests an implementation of the Clausius-Clapeyron relation, applying a simple temperature-based scaling to existing flood estimate values using equation 1:

$$I_p = I_{ARR} \times (1 + \frac{CC}{100})^{T_m} \tag{1}$$

where: I_p = projected rainfall intensity (e.g. 10 mm/hour); I_{ARR} = historical rainfall intensity (e.g. 10 mm/hour); CC = magnitude of the Clausius-Clapeyron relation expressed as a percentage (default value is 5 %/°C); and T_m = projected mean temperature change.

This method is used in this study to rescale the modelled current climate IFDs to compare against the modelled future climate IFDs. The *CC* values used as inputs for our analyses are 5 % (the default recommended by ARR) and 15 % (the maximum value in the recommended range provided by ARR). The T_m is set to 2.9 °C, corresponding to the mean projected temperature rise reported by Grose et al. (2010) for Tasmania for the end of the Century.

3. Evaluation of model performance

3.1 Comparison of AMAX timeseries

The frequency distributions of AMAX values for the investigated design rainfall durations (0.5, 1, 3, 6, 12 and 24 hours) for both observations and simulated data are qualitatively compared (Fig. 1 and 2). There is generally good agreement in both locations for all durations of 3 hours and longer, with similar shape and magnitude of the frequency distributions. There is significant inter-model variability, explained by the differing boundary conditions of each parent GCM. For both locations, for all durations of 3 hours and longer, the observed data is mostly within the spread of the six models that are considered.

The only exception to this statement is the 24-hour totals for Launceston, which CCAM tends to overestimate by a noticeable margin. This is also true to a lesser extent for the 6- and 12-hour totals (see Table 2). The mean modelled AMAX 24-hour total, averaged across all the models, is 56 mm with a range of 51.4 mm to 58.3 mm, whereas the mean observed AMAX 24-hour total is 41.9 mm. In contrast, for Hobart the simulations follow the observations well for 3-hour through to 24-hour totals, with a peak in the simulated distributions that align well with those observed (Table 2 and Fig. 1).

For all durations below 3 hours, the simulations show a higher percentage difference from observed values. CCAM underestimates the AMAX rainfall for the 0.5-hour and 1-hour totals for both locations, with all models displaying a peak at very light rainfall intensities for these times, and not representing any of the heavier falls (such as >10 mm/0.5 hr or >20 mm/hr). Notably, where the six simulations do not agree with observed values, they do agree with each other, indicating that rather than the boundary conditions provided by the parent GCMs driving this difference, it is more likely to be the limitation of the model resolution and how some aspects of rainfall are parameterised, rather than dynamically resolved, within CCAM.

3.2 Comparison of IFD curves

The IFD curve comparisons (Fig. 3 and 4) support the conclusion that the CCAM model has greater skill for Hobart than it does for Launceston. For Hobart, the modelled IFD values are mostly within 15 % of the observations for the 3- to 12-hour durations (Table 3). Higher frequency AEPs show the highest level of agreement and reduced inter-model variability, especially for 24-hour durations. For the 0.5- and 1-hour durations, the model output underestimates the intensity compared to the observations, with all modelled values differing from observations by more than 30 %.

For Launceston, the 3- and 6-hour duration totals are mostly within 15 % of observations (Table 3). For shorter durations (0.5- and 1-hour duration totals) the model underestimates intensity by >20 % (up to 50 %). For the longer durations (12- and 24-hour) the model output is consistently higher than the observations by more than 25 % (up to 50 %). For both locations, the modelled IFD values tend to agree better with the observed values for the more frequent events (i.e. higher AEPs) as one may expect. This is consistent with the frequency distributions (Fig. 1 and 2) that show better agreement at low to medium rainfall intensities (thus, more common events) compared to the extreme rainfall totals (uncommon events).

Based on the comparisons between observed and modelled AMAX histograms and IFD curves, we conclude that the CCAM model output is consistent with the observations (within 15%) for the current climate at the study locations, supporting the argument that the sub-daily CCAM model output is indicative of the climate in Launceston and Hobart for extreme rainfall durations >3 hours. In Launceston the highest consistency occurs for 3- and 6-hour duration events with AEPs greater than 10 %. In Hobart, there is broader confidence, with model output consistent with observations for 3- to 12-hour durations for all AEPs, and 24-hour AEPs greater than 5%. CCAM, however, underestimates the intensity for the shorter-duration events (0.5- and 1-hour) in both locations and overestimates the intensity for the longer-duration events (12- and 24-

hour), especially in Launceston (consistent with previous work with the 24-hour totals, such as Corney et al. (2010)).

4. Future climate projections

The multi-model assessment generally indicates an increase in rainfall intensity in the future climate at Hobart. The increases in intensity are generally found to be far greater than the default 5 % increase per °C recommended for use by industry in ARR (Table 4 and Fig. 5 and 6). The projected increases are non-linear, with largest increases in short-duration, low frequency AEPs and the lowest increases in the long duration high frequency AEPs. This suggests changes are less likely to be driven by the Clausius-Clapeyron relationship, and far more likely to be driven by climatic changes in the prevailing, rain-carrying synoptic systems in the future (Grose et al., 2012; Grose et al., 2013). This is supported by the multi-model variability, as the models generally agree on the magnitude of climate warming (Corney et al., 2010), but have different representations of the dominant synoptic features. In both locations, there is significant inter-model variability, with MIROC3.2(medres) consistently projecting minimal change into the future, while UKMO-HadCM3 projects large increases in rainfall intensity (up to 200 % in some of the lower AEP classes). This large variability in projected rainfall intensity across the different GCMs is the product of emergent features of the models such as differing mean position of the subtropical ridge, driving different dominant synoptic patterns across the state in the different models (Bennett et al., 2014). This model spread shown in Fig. 5 and 6 indicates that it is these changes in the dynamic processes into the future, resulting in heavier rainfalls, that are more important than the temperature-driven changes to the water holding capacity of the atmosphere.

The different dominant synoptic patterns within each model also influence the point-based assessment used in this study, as the distribution and mean rainfall of the target grid cell is affected. Further, Hobart and Launceston are in different climatic regions of Tasmania, and will be influenced by any change in the subtropical ridge in different ways, which is discussed separately below.

While Hobart receives a high proportion of its rainfall from persistent westerlies, a significant fraction of its annual rainfall occurs in episodic, higher-intensity easterly systems (Fox-Hughes and White, 2015). These systems are by their nature more variable and less predictable than the prevailing westerly conditions. The multi-model spread (see Fig. 5) reflects the range of plausible futures and suggests there is some uncertainty in the exact magnitude of response. CCAM projects 40 to 60 % increases in the intensity of short duration events, and 20 to 30 % increases in longer duration events (Table 4) based on a 2.9 °C temperature change. The magnitudes of these changes are closer to a 15 % increase per °C for short duration events, far exceeding the 5 % default increase per °C recommended by ARR. Additionally, there is significant overlap between historical and future model output, decreasing the certainty of significant changes in the future.

In contrast to Hobart, Launceston has almost no overlap between the current climate model simulations and the future model projections, indicating a far more distinct increase in rainfall intensities around Launceston. Launceston receives rainfall from both northwesterly and northeasterly systems. As Launceston is further north than Hobart, any change in the position of the subtropical ridge will be felt more acutely, and this is likely reflected in these results. CCAM projects 40 to 120 % increases in the intensity of short-duration events, and 20 to 80 % increases in longer-duration events (Table 4). These greatly exceed the 5 % increase per °C recommended by ARR (Fig. 6), although the largest increases carry with them very low confidence. Focusing on just the durations and AEPs for which we have reasonable confidence (3- to 6-hour AEPs >10 %), the projected increases are more reasonable, ranging from 20 to 50 %.

The future rainfall intensities show an especially significant increase from current conditions for Launceston. Here, the *CC* temperature scaling estimates are under predictions even for the 24-hour duration and especially for the less frequent (lower AEP) events. For example, our average modelled results indicate that the 1 % AEP 3-hour design rainfall event for Launceston could become twice as intense in the future climate (top left plot of Fig. 6). Although there exists significant spread among models for this projection, not one model projects that the increase in intensity will be lower than that estimated by 5 % scaling.

In short, our results highlight two main patterns in the divergence between the observed and modelled IFD curves: (1) the temperature scaling projections based on 5 % scaling (purple dotted lines) align well with the modelled projections for the highest AEPs and for the 24-hour duration, and (2) the scaling estimates then diverge from the modelled projections for the shorter-duration and less frequent events. There is significant multi-model spread for Launceston, but the modelled results show almost universally that the future rainfall intensities will be higher than what would be expected based on *CC* scaling alone.

5. Discussion and conclusions

In this study, we describe the skill of the CCAM regional climate model in reproducing sub-daily rainfall extremes for Tasmania, and examine projections for future sub-daily values. CCAM is a convection-parametrizing rather than convection-permitting model, and therefore we did not expect the results regarding very short durations (i.e. <1-hour) to be simulated with much skill. Thus, the central aim of this study was to answer the following question: what is the shortest duration at which a convection-parametrizing RCM produces plausible extreme rainfall IFDs?

At our two test locations of Hobart and Launceston in Tasmania, Australia, we find that CCAM accurately simulates sub-daily extreme rainfall events with durations down to around 3 hours when compared with long-term observations. This result is notable given that CCAM is not a convection-parametrizing model and that a bias-correction was not performed on the data for this study, whereas bias-correction has previously been required for accurate results at longer 24-hour durations (e.g. Bennett et al., 2014; Li et al., 2017). These results run counter to previous studies that suggest that very high-resolution convection-permitting models are needed to accurately reproduce sub-daily extreme rainfall events (e.g. Chan et al., 2014b; Westra et al., 2014; Johnson et al., 2016; Kendon et al., 2017). We are not suggesting that this previous work is incorrect; rather, we are providing evidence that in some cases, extreme rainfall statistics can be accurately reproduced without using a computationally expensive convection-permitting model.

The results of this study suggest that model skill likely occurs because the extreme rainfall experienced in the study locations, while often convective in nature, occurs as part of larger frontal systems and extratropical cyclones that are modelled with sufficient accuracy within

CCAM (Corney et al., 2010), which means the relative skill of CCAM may be partially location-specific. The differences between modelled and observed values for shorter (i.e. < 3-hour) durations therefore occur because these shorter-period extremes are the result of convective behaviour within larger systems that are not well modelled by CCAM's ~10 km grid. It is generally assumed that a 1 km or smaller grid scale is needed to use a convection-permitting scheme (Westra et al., 2014).

Another reason for the model skill is that CCAM is a dynamically downscaled model rather than relying on a statistical scheme to generate local-scale weather phenomena. Several studies have compared the results of statistical and dynamical downscaling, showing that the two methods perform similarly for current climate, but dynamically downscaled models have been shown to be more accurate at producing regional climate change signals (Cubasch et al., 1996; Corney et al., 2013). Dynamical downscaling allows for changes in the local climate, such as changes to seasonality, changes to the frequency and intensity of weather events and the relationships between different climate variables. This behaviour is essential for modelling changes to sub-daily extreme rainfall totals.

One area where our results are somewhat counterintuitive is that CCAM reproduces trends that are closer to observations for Hobart than for Launceston. One would expect the Launceston results to be more reliable as Launceston is relatively flat and far from the ocean, whereas Hobart is a port city on the flank of a mountain. The reason for the increased skill in Hobart could lie in the type of rain-producing weather systems seen in this region. Extreme rainfall events in and around Hobart generally come from extratropical cyclones, which are simulated relatively well by CCAM (Grose et al., 2012). As for Launceston, the lower skill has also been identified by Corney et al. (2010) and Bennett et al. (2014), which show that CCAM over-predicts rain (relative to observations) by as much as 50 % in this region. These studies bias-corrected the daily rainfall to account for this anomaly. As the current study uses uncorrected model output, this difference at the 24-hour duration level was expected. These previous studies also provide possible reasons for the rainfall overestimation for Launceston, the dominant one being Launceston's proximity to multiple mountain ranges. Due to the topography data resolution, the mountains CCAM interacts with are not nearly as steep and high as the actual mountains, so CCAM underestimates the orographic rainfall that occurs in these mountains. The orographic rainfall in the real world depletes atmospheric moisture before storms pass over Launceston, whereas in CCAM, less upstream orographic rainfall occurs. Crucially these studies showed that the reason for this error was systematic and thus should be consistent into the future.

A bias-correction (e.g. following Bennett et al., 2014) could be considered to correct for differences between model output and observations. However, bias-correction at the sub-daily level is problematic due to a lack of gridded sub-daily observations against which the model can be compared. Bias-correction at the sub-daily scale can only be undertaken at sites where observations are available therefore (such as the two sites chosen for this study). This is effectively just scaling the distribution of the model output to match observations over the observational period and assuming this scaling remains consistent into the future. For the current study, we eliminate the need for bias-correction by reporting upon relative changes within the model output when we examine future projections. These changes would be the same even with bias-correction. We do not intend for our projections of future extreme rainfall statistics to be directly used by practitioners; rather, we intend for our study to be a starting point for other studies investigating sub-daily rainfall changes. The key result of our study is the percentage changes in the future projections, not the absolute intensities, which we acknowledge are likely biased in the model. For any future studies that wish to arrive at estimated future rainfall statistics across a wide geographical area for direct use by practitioners, bias-correction of model output will most likely be necessary.

Our findings regarding the projection of future sub-daily extreme rainfall IFDs add to the existing body of research, showing that extreme rainfall events could intensify much more than the simple Clausius-Clapeyron temperature scaling alone predicts, although these findings should be taken within the context of how well the RCM performed against observations at the study locations (Fig. 3 and 4). Existing studies (e.g. Lenderink and van Meijgaard, 2008; Liu et al., 2009) highlight the additional latent heat released from increased atmospheric moisture as a possible key reason for this behaviour. Further, our results confirm that this exaggerated change could be seen mainly in the less frequent, shorter duration events, which has implications for urban applications where short duration extreme events can cause damaging flash floods. Related to this, another important finding is the confirmation that projected increases for daily extreme events cannot be simply extrapolated to sub-daily durations. The CCAM data show that the 1 % AEP 24-hour events will become about 25 % more intense in the future time period examined (White et al., 2010), whereas the sub-daily data used in this study show that the 1 % AEP 3-hour events could become 100 % more intense, if not more (Fig. 5 and 6). This is a conclusion that has been reached by similar studies (e.g. Lenderink and van Meijgaard, 2008).

While our results are promising, they should however be interpreted with some caution. This study focuses on the intensity and frequency of extreme rainfall events, rather than on how accurately these events are simulated from a meteorological processes standpoint. Investigations into the seasonality and meteorological realism of these extreme events could aid model performance and remain an important area for future work. This study is also to some degree location-specific. We suggest that future work should examine whether a regional climate model can produce similarly accurate results for other locations around the world.

In conclusion, while this study may be limited due to the inherent convection-parametrizing nature of the CCAM model used, in many ways this study is an important pedagogic endeavour. We have sought to find the limit of applicability for convection-parametrizing models, and we believe we have found this approximate limit. Our results show that for areas where extreme sub-daily rainfalls do not come principally from convective systems, a convection-parametrizing regional climate model with a ~10 km grid resolution can be skilful at reproducing 'realistic' extreme rainfall statistics for events with 3-hour durations and longer. Further, our results add to the existing research showing that extreme rainfall could increase much more than would be expected by simple temperature scaling in a warming atmosphere. These results are crucial due to the relative cost of high-resolution convection-parametrizing models compared to far less common and far more computationally expensive higher-resolution convection-permitting models. Our results show that in certain situations, planners interested in the effects of climate change can use a model of similar resolution to the one used in this study to get meaningful results, thus saving significant time and money.

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Author's note: These references are in the Journal of Hydrology format, downloaded from the Zotero Style Repository at https://www.zotero.org/styles. The reference list below was then created using Zotero for Mac. The BibTeX file for these references, CFT_IFD.bib, is also attached. It should be noted, however, that in the BibTeX file, the two Chan et al. papers from 2014 are marked as being from 2014, whereas in the reference list below, they are modified to be listed as 2014a and 2014b (the first Chan et al, 2014 entry in the .bib file is the 2014a paper). Also note that the URL for the Bureau of Meteorology (2016) reference is not included in the BibTeX file.

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Tables

Table 1 Description of the GCMs used as boundary conditions for the CCAM model (adapted from Corney et al., 2010).

Global Climate Model (GCM)	Country of origin	Approximate horizontal grid resolution (km)
ECHAM5/MPI-OM	Germany	200
GFDL-CM2.0	USA	300
GFDL-CM2.1	USA	300
MIROC3.2(medres)	Japan	300
CSIRO-Mk3.5	Australia	200
UKMO-HadCM3	United Kingdom	300

Table 2 Results of statistical comparison between observed and modelled AMAX timeseries data for rainfall totals at Hobart and Launceston. Parenthetical values after p-values represent whether null hypothesis that the means of the two datasets are the same and can be rejected at the 95 % significance level. These values are 1 if the null hypothesis can be rejected at the 95 % significance level, and 0 if it cannot be rejected at the 95 % significance level.

Location	**Period (hrs)**	**Observed mean rainfall (mm)**	**Multi-model mean rainfall in mm (range of model means)**	**t-test p-value: ECHAM5 vs observed**	**t-test p-value: GFDL CM2.0 vs observed**	**t-test p-value: GFDL CM2.1 vs observed**	**t-test p-value: MIROC3.2 vs observed**	**t-test p-value: CSIRO vs observed**	**t-test p-value: UKMO vs observed**
Hobart	0.5	9.7	4.6 (4.2-4.9)	2.10E-09 (1)	1.04E-10 (1)	3.19E-09 (1)	1.46E-08 (1)	7.99E-09 (1)	2.40E-09 (1)
Hobart	1	12.5	8.3 (7.5-8.9)	1.61E-05 (1)	6.03E-08 (1)	7.65E-06 (1)	1.40E-04 (1)	7.38E-05 (1)	1.07E-05 (1)
Hobart	3	20.4	18.2 (16.2-19.5)	0.199 (0)	0.002 (1)	0.079 (0)	0.468 (0)	0.531 (0)	0.053 (0)
Hobart	6	27.6	27.2 (24.8-28.7)	0.923 (0)	0.139 (0)	0.835 (0)	0.591 (0)	0.738 (0)	0.643 (0)
Hobart	12	38.6	38.12 (37.1-39.0)	0.891 (0)	0.619 (0)	0.965 (0)	0.995 (0)	0.909 (0)	0.589 (0)
Hobart	24	48.1	49.6 (47.1-52.5)	0.557 (0)	0.903 (0)	0.348 (0)	0.747 (0)	0.449 (0)	0.947 (0)
Launceston	0.5	10.4	5.7 (5.0-6.5)	1.38E-09 (1)	7.65E-13 (1)	3.92E-11 (1)	3.96E-07 (1)	2.60E-08 (1)	4.48E-10 (1)
Launceston	1	13.5	10.1 (9.0-11.5)	2.20E-04 (1)	5.47E-08 (1)	5.35E-06 (1)	0.038 (1)	0.001 (1)	2.16E-05 (1)
Launceston	3	21.4	21.6 (19.6-24.8)	0.944 (0)	0.105 (0)	0.949 (0)	0.034 (1)	0.589 (0)	0.379 (0)
Launceston	6	27.7	32.4 (29.6-36.6)	0.013 (1)	0.122 (0)	0.007 (1)	2.08E-04 (1)	0.024 (1)	0.215 (0)
Launceston	12	34.9	44.9 (41.1-48.4)	1.19E-04 (1)	6.34E-05 (1)	7.61E-06 (1)	4.73E-06 (1)	5.74E-05 (1)	0.002 (1)
Launceston	24	41.9	56.0 (51.4-58.3)	1.58E-05 (1)	5.61E-07 (1)	6.17E-07 (1)	8.02E-07 (1)	6.47E-06 (1)	4.29E-04 (1)

Table 3 Multi-model mean percentage differences (and standard deviation) of IFD intensities for the historical period (1961-2009) compared to observations of the same period at Hobart and Launceston.

Location	Period (hrs)	1 % AEP	2 % AEP	5 % AEP	10 % AEP	20 % AEP	50 % AEP
Hobart	0.5	-69 (5)	-66 (4)	-61 (3)	-58 (3)	-54 (3)	-48 (2)
Hobart	1	-48 (9)	-45 (8)	-41 (6)	-38 (5)	-34 (4)	-30 (4)
Hobart	3	-8 (13)	-9 (10)	-10 (7)	-11 (6)	-11 (6)	-11 (7)
Hobart	6	2 (13)	0 (10)	-1 (6)	-2 (5)	-2 (5)	-2 (6)
Hobart	12	8 (14)	5 (9)	1 (4)	-2 (1)	-3 (1)	-3 (3)
Hobart	24	43 (35)	30 (24)	16 (14)	7 (8)	0 (3)	-5 (2)
Launceston	0.5	-37 (11)	-40 (9)	-44 (7)	-46 (6)	-48 (6)	-47 (4)
Launceston	1	-10 (17)	-16 (14)	-21 (11)	-25 (9)	-27 (7)	-28 (5)
Launceston	3	33 (24)	22 (19)	10 (15)	3 (12)	-2 (10)	-4 (7)
Launceston	6	40 (24)	30 (19)	19 (14)	13 (11)	10 (9)	11 (7)
Launceston	12	52 (28)	41 (20)	30 (13)	24 (10)	21 (7)	23 (5)
Launceston	24	35 (19)	31 (15)	27 (10)	26 (8)	26 (6)	31 (5)

Table 4 Multi-model mean percentage differences (and standard deviation) of IFD values for the projected future period (2070-2090) compared to projected historical period (1961-2009) at Hobart and Launceston based on a projected 2.9 °C temperature increase by the end of the Century.

Location	Period (hrs)	1 % AEP	2 % AEP	5 % AEP	10 % AEP	20 % AEP	50 % AEP
Hobart	0.5	69 (91)	60 (70)	51 (47)	45 (34)	41 (25)	36 (19)
Hobart	1	68 (85)	60 (65)	51 (44)	46 (33)	41 (24)	36 (19)
Hobart	3	57 (73)	51 (55)	45 (37)	41 (27)	39 (22)	34 (20)
Hobart	6	61 (50)	53 (39)	45 (28)	40 (23)	35 (21)	30 (20)
Hobart	12	52 (48)	46 (37)	39 (27)	34 (21)	30 (18)	24 (17)
Hobart	24	35 (40)	31 (30)	28 (19)	26 (14)	23 (13)	20 (15)
Launceston	0.5	122 (136)	101 (102)	79 (65)	66 (44)	55 (27)	42 (16)
Launceston	1	117 (146)	95 (105)	73 (64)	61 (40)	51 (24)	39 (16)
Launceston	3	118 (158)	92 (108)	68 (62)	54 (39)	43 (23)	31 (12)
Launceston	6	100 (154)	79 (104)	59 (58)	48 (34)	39 (19)	29 (11)
Launceston	12	88 (107)	68 (73)	49 (41)	39 (25)	31 (14)	24 (7)
Launceston	24	80 (69)	64 (50)	47 (31)	37 (20)	30 (12)	22 (6)

Figure Captions

Fig. 1 Frequency distributions of AMAX rainfall totals at Hobart showing the comparison between observed data and each of the six downscaled models for 1961-2009. Bins are automatically selected in order to provide a smooth histogram.

Fig. 2 As for Fig. 1 but for Launceston.

Fig. 3 Intensity-Frequency-Duration curves at Hobart showing the comparison between observed and multi-model mean for 1961-2009. Curves are generated using GEV fits.

Fig. 4 As for Fig. 3 but for Launceston.

Fig. 5 Intensity-Frequency-Duration curves at Hobart showing the comparison between the multi-model means for the current (1961-2009) and future (2070-2099) climate. Dotted lines show projected rainfall changes based on a simple temperature scaling approach of 5 % and 15 % increase.

Fig. 6 As for Fig. 5 but for Launceston.

For Appendix:

Fig. A.1 Frequency distributions of differing rainfall totals at Hobart, showing the comparison of observed and modelled 0.5, 1, 3, 6, 12 and 24-hour durations for 1961 to 2009.

Fig. A.2 As for Fig. A.1 but for Launceston.

Fig. A.3 Observed and single model AMAX curves with GEV fits for Hobart for 1961-2009; 3-hour rainfall totals.

Fig. A.4 Observed and single model AMAX curves with GEV fits for Hobart for 1961-2009; 6-hour rainfall totals.

Fig. A.5 As for Fig. A.3 but for Launceston.

Fig. A.6 As for Fig. A.4 but for Launceston.